Mapping & pre-empting COVID-19 disinformation in Canada
Acknowledgement

The Mapping & pre-empting COVID-19 disinformation in Canada research and report are prepared by Iris Communications (www.IrisComms.ca).

Gareth Ham, Director of Digital Strategy and Data Analytics, Iris Communications, is the Chief Methodologist and Lead Researcher.

The Mapping & pre-empting COVID-19 disinformation in Canada research and report was undertaken with funding from Canadian Heritage's Digital Citizen Contribution Program. The Digital Citizen Contribution Program supports third-party organizations undertaking research or citizen-focused activities, such as public awareness tools and online workshops, to help Canadians become more resilient and think critically about the information they consume online. For more information on the Digital Citizen Contribution Program visit, https://www.canada.ca/en/canadian-heritage/services/online-disinformation/digital-citizen-contribution-program.html.
## Contents

1.0 Abstract ................................................................................................................................. 5  
   1.1 Abstract .......................................................................................................................... 5  
   1.2 Résumé analytique ......................................................................................................... 6  

2.0 Summary ................................................................................................................................... 8  
   2.1 Summary ....................................................................................................................... 8  
   2.2 Sommaire ...................................................................................................................... 12  

3.0 Methodology .................................................................................................................................. 17  
   3.1 Data .................................................................................................................................. 17  
   3.2 Software .......................................................................................................................... 23  
   3.3 Graph theory ................................................................................................................... 25  
   3.4 The simplified graph theory process .................................................................................. 32  
   3.5 The graph explained ........................................................................................................ 38  
   3.6 The search query ............................................................................................................. 39  
   3.7 Final query ....................................................................................................................... 43  
   3.8 Data gathering .................................................................................................................. 44  
   3.9 Data integrity ................................................................................................................... 46  

4.0 Network analysis ....................................................................................................................... 48  
   4.1 The Twitter network ....................................................................................................... 48  
   4.2 Communities .................................................................................................................... 49  
   4.3 Segmentation branches ................................................................................................... 52  
   4.4 Language .......................................................................................................................... 54  
   4.5 Country distribution ........................................................................................................ 57  
   4.6 Provincial distribution ..................................................................................................... 60  
   4.7 Suspected automation ...................................................................................................... 62  
   4.8 Active accounts .............................................................................................................. 64  
   4.9 Post volume ...................................................................................................................... 65  
   4.10 Daily mentions ............................................................................................................... 67  
   4.11 Gender ............................................................................................................................ 69  

5.0 The geographic and government clusters .............................................................................. 71
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1 British Columbia</td>
<td>71</td>
</tr>
<tr>
<td>5.2 Alberta</td>
<td>71</td>
</tr>
<tr>
<td>5.3 Government</td>
<td>72</td>
</tr>
<tr>
<td>5.4 Ontario</td>
<td>72</td>
</tr>
<tr>
<td>6.0 The political clusters</td>
<td>74</td>
</tr>
<tr>
<td>6.1 Progressive</td>
<td>74</td>
</tr>
<tr>
<td>6.2 Right-Wing</td>
<td>76</td>
</tr>
<tr>
<td>6.3 Rebel News</td>
<td>80</td>
</tr>
<tr>
<td>6.4 Anti-Liberal</td>
<td>83</td>
</tr>
<tr>
<td>6.5 The Québécois fringe</td>
<td>86</td>
</tr>
<tr>
<td>7.0 Issues of race, sexuality and Indigenous Canadians</td>
<td>89</td>
</tr>
<tr>
<td>8.0 A brief note on the web network</td>
<td>94</td>
</tr>
<tr>
<td>9.0 Beyond this project</td>
<td>96</td>
</tr>
<tr>
<td>9.1 Response strategies</td>
<td>97</td>
</tr>
<tr>
<td>9.2 Further analysis</td>
<td>100</td>
</tr>
<tr>
<td>9.3 Forensic analysis</td>
<td>104</td>
</tr>
</tbody>
</table>
1.0 Abstract

1.1 Abstract

This project is a study of online data. More than 53 million individual conversations were analysed, in the period of March 1 to December 31 2020, that addressed the topic of COVID-19 in Canada. Outputs were threefold. Firstly, we explain how the project was undertaken, and the iterations of the methodology, so that it can be reconstructed as a product in the future. Secondly, in order to prove the concept of the methodology, and also to provide a navigation tool for subsequent projects, a top-level analysis of the major communities and narratives within Canadian COVID-19 conversation was undertaken. In short, the methodology provides the online ‘locations’ that are more likely to be the source and space of proliferation of disinformation narratives. Lastly, the report clearly outlines practical ways in which this research should be used in the future, and areas for expansion.

Initially, this work was planned to be a study of the changing disinformation narratives in Canada over 2020, involving a comparison of the beginning and end of the year. However, due to the timeframe involved, it was decided to change direction slightly. By the project’s delivery, much of the online conversation (and therefore opinions of Canadians) around the pandemic were more than a year old. With a topic as fast-moving as COVID-19, and its news cycle, and the emergence of new topics around vaccines, travel, and restrictions, for example, the opinions of Canadians in March 2020 have little bearing on the online climate at the end of 2021. Therefore, much of the project’s resource was dedicated to building a robust, scalable, and replicable methodology that could be used to uncover and analyse topics of disinformation into the future. The methodology has been specifically designed for this purpose.

The output, however, should not be viewed merely as a methodology, but as a complete road map to analysing future disinformation in Canada, around almost any topic, that can be installed quickly, cheaply and without computer programming. To this end, it is a tool ready to be used with little complexity, that will undoubtedly increase resilience in fighting disinformation at a national level.

This methodology was proved by human analysts. Following the initial segmentation of Canadian COVID-19 online conversation, human analysts examined the conversations, their authors and the key media involved in each online community, in order to prove the concept. The objective was to define a data analysis methodology to find areas of the public web where disinformation narratives are more likely to pervade, and this was achieved. As the nature of Canadian online usage and discourse changes more generally, our understanding of where disinformation narratives might be found will also change, but we expect this to happen relatively slowly and to be discoverable by exactly the same methodology.

The next step is to share this information with willing participants, inside and outside government, in order to see its effectiveness realized in the wider world. This report outlines, at length, a range of ways in which these findings
need to be used by government departments and agencies to fight disinformation narratives in the online and offline worlds. Partnerships need to be explored with organisations that have the means and resources to use these findings in the most meaningful way possible.

### 1.2 Résumé analytique

Ce projet consiste en une étude de données recueillies en ligne. Pendant la période du 1er mars au 31 décembre 2020, plus de 53 millions de conversations individuelles ont été analysées, qui abordaient le sujet du COVID-19 au Canada. Les résultats comportaient trois volets. Tout d'abord, nous expliquons comment le projet a été entrepris, et les différentes étapes de la méthodologie, afin qu'il puisse être reconstruit en tant que produit à l'avenir. Deuxièmement, afin de vérifier le principe de la méthodologie et de fournir un outil de navigation pour les projets suivants, une analyse de pointe a été entreprise des principales communautés et des principaux discours de la conversation canadienne sur COVID-19. En bref, la méthodologie fournit les soi disant endroits en ligne qui sont les plus susceptibles d'être la source et l'espace de prolifération des récits de désinformation. Enfin, le rapport présente clairement les moyens pratiques d'utiliser cette recherche à l'avenir, ainsi que les pistes à explorer.

Dans un premier temps, il était prévu que ce travail soit une étude de l'évolution des discours de désinformation au Canada au cours de l'année 2020, qui comprendrait une comparaison entre le début et la fin de l'année. Cependant, en raison des contraintes de temps, on a décidé de changer légèrement d'orientation. Au moment de la réalisation du projet, la plupart des conversations en ligne (et donc des opinions du public canadien) sur la pandémie dataient de plus d'un an. Avec un sujet qui évolue aussi rapidement que COVID-19, et la diffusion constante des nouvelles, et la parution de nouveaux sujets autour des vaccins, des voyages et des restrictions, par exemple, les opinions des Canadiens et Canadienses en mars 2020 ont peu d'influence sur le climat en ligne à la fin de 2021. Par conséquent, une grande partie des ressources du projet ont été consacrées à l'élaboration d'une méthodologie robuste, évolutifre et reproductible qui pourrait être utilisée pour découvrir et analyser les sujets de désinformation à l'avenir. La méthodologie a été spécifiquement conçue à cette fin.

Toutefois, le produit ne doit pas être considéré comme une simple méthodologie, mais comme une feuille de route complète pour l'analyse de la désinformation future au Canada, sur presque tous les sujets, qui peut être mise en place rapidement, à peu de frais et sans programmation informatique. À cette fin, il s'agit d'un outil prêt à être utilisé avec peu de complexité, qui augmentera sans aucun doute la résilience dans la lutte contre la désinformation au plan national.

Cette méthodologie a été vérifiée par des analystes humains. Après la segmentation initiale des conversations canadiennes en ligne sur le COVID-19, des analystes humains ont examiné les conversations, leurs auteurs et les principaux médias impliqués dans chaque communauté en ligne, afin de vérifier le concept. L'objectif était de définir une méthodologie d'analyse des données pour trouver des zones du Web d'accès public où les récits de
désinformation sont plus susceptibles de se répandre, et cet objectif a été atteint. Au fur et à mesure que la nature de l'utilisation et du discours en ligne au Canada évolue, notre perception des endroits où l'on peut trouver des récits de désinformation changera également, mais nous pensons que cela se produira relativement lentement et qu'il sera possible de les découvrir avec exactement la même méthodologie.

L'étape suivante consiste à partager ces informations avec des participants disposés à le faire, à l'intérieur et à l'extérieur du gouvernement, afin de voir son efficacité se concrétiser dans un contexte plus étendu. Le présent rapport décrit en détail une variété de moyens par lesquels ces résultats devraient être utilisés par les ministères et les agences gouvernementales pour lutter contre les récits de désinformation dans les mondes en ligne et hors ligne. Il faut envisager des partenariats avec des organisations qui ont les moyens et les ressources nécessaires pour utiliser ces résultats de la manière la plus significative possible.
2.0 Summary

2.1 Summary

This report is a plan. A blueprint. A recipe. It outlines a technological and methodological strategy to identify and understand the issue of online disinformation in Canada, and where it impacts Canada and Canadians. Disinformation on public social media is a moving target: narratives, bad actors and even specific platforms change over time, either deliberately, within the tactics of sowing disinformation, or simply due to digital evolution. This report has gathered data on public conversations since the beginning of COVID-19 in Canada (early 2020) and analysed these conversations, but our focus cannot be solely on these findings, due to the amount of time that has passed. For this document to be useful into the future, it needed to focus on the fundamentals of detection and analysis; on how software can be acquired and used in the most effective ways; on how we use open-source methodologies to better understand why and how disinformation changes decision-making and behaviour in Canada, and how the country has been ‘segmented’ along factional lines in the fight against COVID-19.

This document is therefore presented in three distinct sections. Firstly, a detailed methodological chapter, not simply to underscore the legitimacy of the report’s conclusions, but to present a strategy of how it can be recreated quickly, simply, consistently and without error, with its information disseminated to agencies that can use it practically. The methodology built to understand the issue of COVID-19 in Canada has its roots in established social listening, social media analysis and network analysis techniques that have evolved over the last decade, but it has been almost entirely configured for the analysis of this specific topic in this specific scenario. It is presented here in full.

A distinct focus of this methodology is on its use of open source, or off-the-shelf, technologies. This process has deliberately shunned proprietary technology, data ‘scraping’ techniques or ‘favours’ with data providers, due to inherent unreliability. Similarly, the team behind this report has not built any software or widgets dedicated to this task; all tools can be, and are in the main, used for more general analysis of social media, away from the subject of disinformation. Lastly, the methodology relies little on manual analysis, manual categorization (or coding) of data, or manual data ‘inferences’, largely due to a focus on timeliness and future consistency. Such techniques need to be replicable quickly, accurately and cheaply.

Secondly, this report analyses the data captured on the subject of COVID-19 in Canada from January 1 to December 31, 2020, with a more detailed focus on the period from March 1 onwards with proportionally few conversations on the subject detected before this date. The dataset of 53 million public online ‘conversations’ was captured from a multitude of open-source online locations, and comprised social media, news, blogs, forums, image and video sites, and other areas of the web that are difficult to discreetly categorize (in part, due to their
nefarious nature). These 53 million ‘mentions’ encompassed the whole subject of COVID-19 with respect to Canada in the reporting period, as opposed to simply discussions of perceived disinformation, for two primary reasons: firstly, we need the context of the entire conversation to understand the role of disinformation in Canadian discourse; and secondly, a tenet of this methodology is fact, we cannot anticipate or approximate narratives, social media entities or media used to sow disinformation. In short, in lieu of ‘guessing’ tactics of disinformation, we captured everything. Data that was captured also reflected the global nature of online discussions. We needed to analyse online narratives and tactics that sought to influence Canadians around the issue of COVID-19. Therefore, data captured conversations both posted by Canadians, and about COVID-19 in Canada.

At a macro level, this analysis found the following:

Within Twitter conversation, nine primary communities were identified in Canadian social media around COVID-19. These communities formed along geographic, linguistic and political lines, with what we might call ‘mainstream’ political views on the pandemic segmented by provincial issues, whilst on the extremes, far right political parties and figures helped to shape their own online ‘factions’.

Within far-right elements of the COVID-19 discussion, publications such as Rebel News, with Ezra Levant as its principal antagonist, dominated discourse and helped to shape opinions. Sources from the United States were also prevalent in driving the conversation around the right-wing fringes, with around only 30% of this neighbourhood generated by domestic, Canadian sources, compared to around 60% confirmed across the rest of the network.

A distinct French-language neighbourhood was identified in the network, almost detached from the rest of the network. This shows that, as perhaps expected, COVID-19 conversation in Canada is linguistically divided. The ‘Quebecois’ cluster in the network contributed 7% of the entire network. French language-centric online entities (those for whom French is used more than English) contributed 7.4% of the network, due to the presence of French speakers, in a tiny minority, elsewhere in the network, notably in the ‘Government’ cluster.

In the rest of the network, Ontarian, Albertan and British Columbia-related conversations each generated locally distinct communities, showing the importance of provincial politics and decision-making in the COVID-19 discussion. The Ontario neighbourhood was the second largest in the network, contributing nearly a fifth (17%) of all entities.

Obvious automation in the network was low. Just 6% of all entities in the network were suspected to be automated, a small proportion compared to many political and social media discussions, in Canada and aboard.

The ‘anti-Liberal’ cluster was more likely to post about COVID-19 than any other cluster: contributing more than twice per entity, per day of the reporting period. Entities on the political left, however, posted in heavier quantities than any other cluster when we consider all conversation. This neighbourhood posted, on average, more than 30 times per account, per day of the reporting period on all subjects.
In every cluster in the network, entities that identified as male were more likely to post than those that identified as female. The Left neighbourhood was the most skewed, at nearly two-thirds male (66%).

Lastly, this report looks to the future. If the methodology chapter of this document looks at how we approached this task and steps we will take thereafter, the Beyond this project chapter analyses where we might wish to point this methodology in 2021, and later.

Potential next steps can be filed under three headings. Firstly, how we use this exact data to inform response strategies. This can be undertaken either at a micro or macro level. At the micro level, keywords, phrases, accounts or patterns of communication trigger software alerts to human beings making decisions. Responses can then be activated in the short-term to counter narratives and disrupt malign influence operations. At a macro level, ongoing analysis should be used to define counter narratives and strategies aimed at doing everything from running online campaigns that target the right communities with factual information, to instigating far-reaching media literacy initiatives in schools and among the wider public. This is increasingly important as the COVID-19 debate evolves to take in vaccines, international and interprovincial travel, ‘COVID passports’ and a variety of responses at a provincial, and even city level, in addition to Federal legislation.

Secondly, the report investigates areas that could be subject to further analysis, within the gamut of an analysis of 53 million conversations. Technological advancements in the areas of image detection, video frame-by-frame recognition, and media manipulation analysis to better detect ‘deep fakes’, for example, can be utilized to advance this research, to understand more about influence campaigns and their tactics, and to better counter them. More ambitious ‘big data’ analysis should also be an area of focus: whilst this study looked at 53 million mentions online, it still represents a tiny fraction of what is out there. Is there a way to take the pulse of the general public beyond the specific issue of where people are talking about COVID-19? Can we extend this to wider areas of concern around Canadian security in the wider world, public ‘happiness’ or economic forecasting by processing more data? Similarly, this project can provide raw data precisely so that it might be merged with other datasets in the future. These datasets could be in the form of offline opinion polling, security analysis, or even weather or economic indicators. The list is almost endless, but the question is succinct: how might we manipulate our data further to better understand Canada?

Lastly, there is significant room to be more ‘forensic’ in this field. Organisations and academics around the world are increasingly looking at the area of Open-Source Intelligence (OSINT) to more categorically attribute influence operations, trace them to their financial origins and work with security agencies to ‘name and shame’. In the wider battle against disinformation and those entities that ride its coattails, meaningful action can only be taken by governments and supranational organisations if most, if not all, of the doubt is removed at the attribution stage. Analysis such as that undertaken in this project can get some of the way there, but the next step involves time-consuming, dogged scrutiny of subjects of interest and their online and offline activity: following the paper trail. It requires knowledge of darker areas of the internet than Twitter, and knowledge of the data extraction techniques
required. It also often requires an ability, and a constitution, to work in the dark, on the frontlines. This project shows the way towards that path. Or, perhaps more descriptively, it shows the locations of the trailheads. But the next steps must be taken by OSINT experts.

The fight against disinformation has long been compared to the fairground game of whack-a-mole: destroy one narrative, one bad actor or even a whole botfarm, and countless more emerge in their place. Deploy studies and investigations to better understand the tactics of these influence operations, and their methods diversify and mutate further. In fact, many influence operations in the last few years have ‘priced this in’, considering account suspensions, and government and platform counter attacks merely collateral damage. On the surface, counter-disinformation can appear to be a fruitless endeavour. However, disinformation relies on both supply and demand. There is an audience receptive to disinformation: for reasons of society, of economy, or of political alienation and disenfranchisement. This audience has been further shaped and distanced by phenomena inherent to the internet and social media as a whole: notably filter bubbles, financial-incentivised algorithms, ‘autoplay’ features and the prioritization of metrics by social media platforms. In a possibly reductive way, we might understand that online disinformation fills a gap.

This is especially true as disinformation and influence campaigns move beyond outright lies and deceit, and find fertile ground in existing social cleavages, seeking to further widen these gaps and to divide society. This was witnessed as early as 2016, when analysis of data by Twitter of the US Presidential election found that botnets were often found to support Democratic Candidate Hillary Clinton, in addition to Republican Donald Trump\(^1\). Or later, when the Mueller Report noted increased Russian involvement on both sides of the Black Lives Matter hashtag battle on social media platforms\(^2\).

It is therefore posited by this report that the key to understanding emerging disinformation threats is to understand the prevailing segmentation, and ‘factionalization’, of social media in Canada around issues of public interest. The structure of debate in Canada is something that is stable in comparison to individual online disinformation narratives and tactics. As the debate evolves and takes in vaccination attitudes, and as the country re-opens, the ‘structure’ of the online debate has remained largely the same, framed by political parties, centres of influence in the United States, and deeper social ‘identities’ that are far more important in terms of determining one’s location in the Canadian COVID-19 debate than the often-nuanced aspects of virology and epidemiology. In fact, that these online ‘factions’ are seemingly so entrenched, driven by the paramount importance of online ‘identities’, can possibly be viewed as a positive in terms of online analysis and response. Understanding the Canadian online landscape is essential to countering disinformation.

---

\(^2\) https://intelligence.house.gov/social-media-content/
The methodologies and techniques presented in this document should therefore be seen as the beginning of a new approach that could be taken to analyse an evolving, moving target, rather than providing a definitive set of answers to an incredibly complex issue.

2.2 Sommaire

Ce rapport représente un plan, un schéma directeur et une recette. Il décrit une stratégie technologique et méthodologique qui permet d'identifier et de comprendre le problème de la diffusion de la désinformation sur Internet au Canada, ainsi que son impact sur le Canada et ses citoyens. La désinformation sur les médias sociaux publics est une cible mobile : les récits, les mauvais opérateurs et même certaines plateformes changent au fil du temps, soit délibérément, dans le cadre de la tactique consistant à semer la désinformation, soit simplement en raison de l'évolution numérique. Ce document présente des données sur les conversations publiques observées depuis le début de COVID-19 au Canada (début 2020) et notre analyse de ces conversations, mais nous ne pouvons pas nous concentrer uniquement sur ces résultats, en raison du temps qui s'est écoulé. Pour que ce document soit utile à l'avenir, il fallait qu'il se concentre sur les principes fondamentaux de la détection et de l'analyse ; sur la façon dont les logiciels peuvent être acquis et utilisés de la manière la plus efficace ; sur la façon dont nous utilisons les méthodologies de source ouverte pour mieux comprendre pourquoi et comment la désinformation modifie la prise de décision et le comportement au Canada, et comment le pays a été dé coupé selon les lignes de fracture politiques dans la lutte contre COVID-19.

Ce document est donc présenté en trois chapitres distincts. Tout d'abord, un chapitre méthodologique détaillé, non seulement pour souligner la légitimité des conclusions du rapport, mais aussi pour présenter une stratégie sur la façon dont il peut être reconstitué rapidement, simplement, de manière cohérente et sans erreur, et dont les informations puissent être diffusées aux organismes qui peuvent s'en servir de manière pratique. La méthodologie mise au point pour comprendre la question du COVID-19 au Canada s'appuie sur des techniques établies d'écoute attentive de la société, d'analyse des médias sociaux et d'analyse de réseau qui ont évolué au cours de la dernière décennie, mais elle a été presque entièrement configurée pour l'analyse de ce sujet spécifique dans ce scénario spécifique. Elle est présentée ici dans son intégralité.

Cette méthodologie met l'accent sur l'utilisation de technologies à source ouverte, ou prêtes à l'emploi. Nous avons délibérément évité les technologies propriétaires, les techniques de grattage de données ou les f aveurs accordées par les fournisseurs de données, en raison de leur manque de fiabilité intrinsèque. De même, l'équipe à l'origine de ce rapport n'a pas construit de logiciels ou de dispositifs conçus spécialement pour cette tâche ; tous les outils peuvent être, et sont dans l'ensemble, utilisés pour une analyse plus générale des médias sociaux, à l'écart du sujet de la désinformation. Enfin, la méthodologie s'appuie peu sur l'analyse manuelle, la catégorisation (ou le codage) manuelle des données ou les inférences manuelles des données, en grande partie parce que l'accent est mis sur la rapidité et la cohérence future. Ces techniques doivent pouvoir être reproduites rapidement, avec précision et à un prix abordable.
Deuxièmement, ce rapport analyse les données saisies sur le sujet du COVID-19 au Canada du 1er janvier au 31 décembre 2020, avec un regard plus approfondi sur la période à partir du 1er mars, le nombre de conversations sur le sujet repérées avant cette date étant proportionnellement faible. L'ensemble de données de 53 millions de conversations publiques en ligne a été capturé à partir d'une multitude d'emplacements en ligne ouverts, et comprenait des médias sociaux, des nouvelles, des blogs, des forums, des sites Internet de diffusion d'images et de vidéos, ainsi que d'autres zones du Web qui sont difficiles à mettre en catégories nettement distinctes (en partie, en raison de leur nature malveillante). Ces 53 millions de commentaires englobaient l'ensemble du sujet COVID-19 concernant le Canada au cours de la période considérée, par opposition aux simples discussions sur la désinformation présumée, pour deux raisons principales : premièrement, nous avons besoin du contexte de l'ensemble de la conversation pour comprendre le rôle de la désinformation dans le discours canadien ; et deuxièmement, comme le veut cette méthodologie, nous ne pouvons pas anticiper ou établir une approximation des récits, des entités de médias sociaux ou des médias utilisés pour semer la désinformation. En bref, au lieu de deviner les tactiques de désinformation, nous avons tout enregistré. Les données saisies témoignaient également de la nature mondiale des discussions en ligne. Nous devions analyser les récits et les tactiques en ligne qui cherchaient à influencer les Canadiens sur la question du COVID-19. Par conséquent, les données ont capturé des conversations affichées par des Canadiens et portant sur le COVID-19 au Canada.

D'une vue d'ensemble, cette analyse a permis de constater ce qui suit :

Dans le cadre des conversations sur Twitter, neuf communautés principales ont été identifiées dans les médias sociaux canadiens au sujet de COVID-19. Ces communautés se sont formées suivant des orientations géographiques, linguistiques et politiques, avec ce que l'on pourrait appeler des opinions politiques prédominantes sur la pandémie, subdivisées en fonction des questions provinciales, tandis qu'aux extrêmes, des partis et des personnalités politiques d'extrême droite ont contribué à former leurs propres confréries en ligne.

Au sein des éléments d'extrême droite de la discussion concernant le COVID-19, des publications telles que Rebelnews, avec Ezra Levant comme principal antagoniste, ont dominé le discours et contribué à formuler les opinions. Les sources américaines ont également joué un rôle prépondérant dans la conversation autour des marges de l'extrême droite, avec seulement 30 % de ce groupe généré par des sources canadiennes, contre environ 60 % confirmés dans le reste du réseau.

Un groupe distinct de langue française a été identifié, presque détaché du reste du réseau. Cela montre que, comme on pouvait s'y attendre, la conversation sur le COVID-19 au Canada est divisée sur le plan linguistique. Le groupe québécois du réseau a contribué 7% de l'ensemble du réseau. Les entités centrées sur la langue française (celles pour lesquelles le français est plus utilisé que l'anglais) ont contribué jusqu'à 7,4% du réseau, en raison de la présence de francophones, en très faible minorité, ailleurs dans le réseau, notamment dans le regroupement Gouvernement.
Dans le reste du réseau, les conversations liées à l'Ontario, à l'Alberta et à la Colombie-Britannique ont chacune généré des communautés localement distinctes, ce qui montre l'importance de la politique et des mécanismes décisionnels provinciaux dans la discussion sur le COVID-19. Le groupe de l'Ontario était le deuxième plus important du réseau, contribuant à peu près d'un cinquième (17%) de toutes les entités.

L'automatisation évidente dans le réseau était faible. Seulement 6 % de toutes les entités du réseau étaient soupçonnées d'être automatisées, une faible proportion par rapport à de nombreuses discussions politiques et de médias sociaux, au Canada et à l’étranger.

Le groupe anti-libéral était plus susceptible de publier des messages sur le COVID-19 que tout autre groupe, contribuant plus de deux fois par entité, par jour de la période de référence. Les entités de la gauche, cependant, ont fait plus de messages que tout autre groupe si l'on considère toutes les conversations. Ce groupe a affiché, en moyenne, plus de 30 fois par compte, par jour de la période considérée, sur tous les sujets.

Dans chaque groupe du réseau, les entités qui s'identifiaient au sexe masculin étaient plus susceptibles d'afficher sur Internet que celles qui s'identifiaient au sexe féminin. Le groupe de gauche était le plus asymétrique, avec près de deux tiers d'hommes (66%).

Enfin, ce rapport se tourne vers l'avenir. Si le chapitre sur la méthodologie de ce document examine la manière dont nous avons abordé cette tâche et les mesures que nous prendrons par la suite, le chapitre intitulé Au-delà de ce projet (Beyond this Project) analyse les orientations que nous pourrions souhaiter donner à cette méthodologie en 2021, et plus tard.

Les prochaines étapes potentielles peuvent être classées sous trois rubriques. Premièrement, examinons comment utiliser ces données exactes pour élaborer des stratégies de réponse. Cela peut se faire dans le détail, où des mots-clés, des phrases, des comptes ou des modèles de communication déclenchent des alertes logicielles vers des personnes qui ont le pouvoir de décision. Des réponses peuvent alors être activées à court terme pour contre les récits et déranger les opérations d'influence malveillante. Sur le plan plus général, l'analyse en cours devrait être utilisée pour définir des contre-récits et des stratégies visant à tout faire, depuis les campagnes en ligne qui ciblent certaines communautés avec des informations factuelles, jusqu'à la mise en place d'initiatives d'éducation aux médias de grande envergure dans les écoles et auprès du grand public. Cette démarche est d'autant plus importante parce que le débat sur le COVID-19 évolue pour englober les vaccins, les voyages internationaux et entre provinces, les passeports COVID et une variété de réponses au niveau des provinces, voire des villes, en plus de la législation fédérale.
Deuxièmement, le rapport examine les domaines qui pourraient faire l'objet d'une analyse plus approfondie, dans le cadre d'une analyse de 53 millions de conversations. Les avancées technologiques dans les domaines de la détection d'images, de la reconnaissance vidéo image par image et de l'analyse de la manipulation des médias pour mieux détecter les hypertrucages, par exemple, peuvent être utilisées pour faire avancer ces recherches, pour mieux comprendre les campagnes d'influence et leurs tactiques, et pour mieux les contester. Une analyse plus ambitieuse des données massives devrait également être envisagée : si cette étude a porté sur 53 millions de commentaires en ligne, elle ne représente qu'une infime partie de ce qui existe. Y a-t-il un moyen d'être à l'écoute du grand public au-delà de la question spécifique de savoir où les gens parlent de COVID-19 ? En traitant davantage de données, pouvons-nous inclure des sujets plus larges comme la sécurité des Canadiens dans le monde, le bonheur du public ou les prévisions économiques ? De même, ce projet peut fournir des données brutes afin qu'elles puissent être fusionnées avec d'autres ensembles de données à l'avenir. Ces ensembles de données pourraient prendre la forme de sondages d'opinion hors ligne, d'analyses de sécurité, ou même d'indicateurs météorologiques ou économiques. La liste est presque infinie, mais la question est claire : comment pourrions-nous manipuler nos données pour mieux comprendre le Canada ?

Enfin, il est possible d'utiliser la criminalistique dans ce domaine. Les organisations et les universitaires du monde entier se tournent de plus en plus vers le domaine du renseignement de sources ouvertes (OSINT) pour attribuer de manière plus catégorique les opérations d'influence, remonter jusqu'à leurs origines financières et travailler avec les agences de sécurité pour les dénoncer. Dans la lutte plus large contre la désinformation et les entités qui en tirent parti, les gouvernements et les organismes supranationaux ne pourront prendre des mesures significatives que si la plupart, voire la totalité, des doutes sont éliminés au stade de l'attribution. Une analyse telle que celle entreprise dans le cadre de ce projet peut permettre d'atteindre une partie de cet objectif, mais l'étape suivante implique un examen minutieux et acharné des sujets d'intérêt et de leur activité en ligne et hors ligne : il faut alors suivre la trace documentaire. Cela nécessite une connaissance de domaines plus sombres d'Internet que Twitter, ainsi qu'une connaissance des techniques d'extraction de données appropriées. Il faut aussi souvent être capable, et avoir la volonté, de travailler dans l'obscurité, en première ligne. Ce projet montre le chemin vers cette voie. Ou, de manière peut-être plus descriptive, il montre l'emplacement des points de départ des sentiers. Mais les prochaines étapes doivent être franchies par les experts en OSINT.

La lutte contre la désinformation a longtemps été comparée au jeu de foire de tape- taupes : la destruction d'un récit, d'un acteur malveillant ou même d'une usine de trolls virtuels en fait surgir un nombre incalculable à leur place. Si l'on mène des études et des enquêtes pour mieux comprendre les tactiques de ces opérations d'influence, leurs méthodes se diversifient et se transforment encore. En fait, au cours des dernières années, de nombreuses opérations d'influence ont intégré le prix de ces risques dans leur planification, et considèrent les suspensions de comptes et les contre-attaques des gouvernements et des plateformes comme de simples dégâts collatéraux. À première vue, la lutte contre la désinformation peut sembler être une entreprise vouée à l'échec. Cependant, la désinformation repose à la fois sur l'offre et la demande. Il existe un public réceptif à la désinformation, pour des raisons sociales, économiques, ou d'aliénation et de marginalisation politiques. Ce
public a été façonné et éloigné par des phénomènes inhérents à l'internet et aux médias sociaux dans leur ensemble : notamment les bulles de sélection par filtre, les algorithmes motivés par la finance, les fonctions de lecture automatique et la hiérarchisation des indicateurs par les plateformes de médias sociaux. D'une manière peut-être réductrice, nous pourrions comprendre que la désinformation en ligne comble un vide.

Cela est d'autant plus vrai que les campagnes de désinformation et d'influence vont au-delà des mensonges purs et simples et trouvent un terrain fertile dans les clivages sociaux existants, cherchant à creuser davantage ces écarts et à diviser la société. On a pu le constater dès 2016, lorsque l'analyse des données Twitter3 de l'élection présidentielle américaine a révélé que les réseaux de zombies soutenaient souvent la candidate démocrate Hillary Clinton, en plus du républicain Donald Trump. Ou plus tard, lorsqu'un travail similaire, The Mueller Report4, a noté une implication russe accrue des deux côtés de la bataille du hashtag Black Lives Matter sur les plateformes de médias sociaux.

Le présent rapport avance donc que la clé pour comprendre les nouvelles menaces de désinformation est de comprendre la segmentation et la division selon des lignes politiques des médias sociaux au Canada autour des questions d'intérêt public. La structure du débat au Canada est relativement stable par rapport aux récits et tactiques de désinformation en ligne. Alors que le débat évolue et prend en compte les attitudes en matière de vaccination, et que le pays rouvre ses portes, la structure du débat en ligne est restée essentiellement la même, encadrée par les partis politiques, les centres d'influence aux États-Unis et des identités sociales plus profondes qui sont bien plus importantes pour déterminer la position d'une personne dans le débat canadien sur le COVID-19 que les aspects souvent controversés de la virologie et de l'épidémiologie. En somme, le fait que ces clans en ligne soient apparemment si bien ancrés, motivés par l'importance primordiale des identités en ligne, peut être considéré comme un élément positif en termes d'analyse et de réponse en ligne. Il est essentiel de comprendre le paysage en ligne canadien pour déjouer la désinformation.

Les méthodologies et techniques présentées dans ce document doivent donc être considérées comme le début d'une nouvelle approche qui pourrait être adoptée pour analyser une cible mobile et en évolution constante, plutôt que de fournir un ensemble définitif de réponses à une question incroyablement complexe.

---


4 https://intelligence.house.gov/social-media-content/
3.0 Methodology

As discussed in the introduction to this document, it has three chief objectives: to understand how we might put in place the methodological building blocks to better monitor and measure disinformation in the Canadian online space; to identify the areas of the COVID-19 discussion on public social media in Canada, and about Canada, from which we can learn; and, thirdly, to understand concrete areas in which the findings of this report can be valuable in the future, either when iterated or moved into related areas of analysis.

As part of this approach, this document details in full the methodological process undertaken. Its aim is to demonstrate how similar tools and techniques can be used in the future, improved, better targeted, shortcut or disregarded entirely. Similarly, the report shows how existing technologies and approaches can be effectively used to understand and analyse the issue of disinformation, and how, rather than intimidating government departments and agencies, analysis of disinformation could be viewed as another communications problem to be solved, using broadly similar techniques.

We might even look at this report as a recipe. Federal, Provincial and Municipal governments across Canada, with the right focus and dedication of resources, can tackle disinformation just as effectively as academic programmes or research organisations. Government often works to a far shorter timeline, with tactical communications or ‘nudge’ tactics in need of refinement daily, making the need to beg, borrow or steal data, analysis methodologies or technology even more of a priority.

3.1 Data

Introduction to social listening

Social listening, frequently referred as social media monitoring or social intelligence, is the practice of collecting, measuring, and analysing open-source data from the public web. Somewhat of a misnomer, social listening also includes areas of the web beyond social media, covering more traditional conversation areas of the internet such as blogs and forums, as well as online news, video image, reviews and ‘below the line’ discussions within these sites. Of course, the nature of the subject being studied impacts the level of reliance on each of these site types: for example, a study of a specific hashtag, a linguistic syntax almost unique to social media for reasons of abbreviation or aggregation of comments, will collect a disproportionately high volume of Twitter or Instagram data than that posted by news articles. The standard social listening ‘currency’ is a ‘mention’. One mention is a single, unique URL that is of interest to our study, as opposed to the number of instances a word is used within an item of media, for example. Hereafter, this report will use the term ‘mention’ when referring to URL data, and its contents, analysed in the study.
According to Wikipedia⁵: “Social media measurement and social media analytics, social listening is a way of computing popularity of a brand or company by extracting information from social media channels, such as blogs, wikis, news sites, micro-blogs such as Twitter, social networking sites, video/photo sharing websites, forums, message boards and user-generated content from time to time. In other words, this is the way to calibrate success of social media marketing strategies used by a company or a brand. It is also used by companies to gauge current trends in the industry. The process first gathers data from different websites and then performs analysis based on different metrics like time spent on the page, click through rate, content share, comments, text analytics to identify positive or negative emotions about the brand.”

The social listening process can be divided in three stages. Firstly, a search query is written to collect data from the public web. A query is written in a database language (check) known as Boolean and consists of a series of logic gates used to simultaneously find matching data and exclude data that breaks specific rules. Boolean in social listening platforms can be used to find or exclude mentions based on semantics, in the form of words, hashtags, emojis or gibberish; to find or exclude mentions based on data contained within a mention such as embedded links or images; or to find or exclude mentions based on the metadata associated with a mention, such as language, location or gender of the account owner.

Secondly, data that matches the search query is collected and brought into a database. Almost always online, the platform that houses the resultant database, a social listening platform, functions as something between an advanced search engine and a light business intelligence tool, such as Tableau. The platform gives the ability to analyse the data in myriad quantitative formats, or to sample or categorise the mentions themselves for qualitative analysis. The database essentially houses a ‘living copy’ of mentions that were collected by the original Boolean search query. ‘Living’, in the sense that edits or changes to the mentions itself will be reflected in the social listening platform: for example, updates to the text of a blog, the links to other pages online embedded in the copy, or metrics associated with the mention, such as Twitter retweets. A “copy”, in the sense that mentions can be marked-up for analysis or bookmarking purposes, and that screenshots of the original mention exist in the platform.

Lastly, comes the analysis process itself. Analysis of social listening data can take infinite forms, with many advanced methodologies outlined in this very report. On the quantitative side, we might simply want to count mentions of a specific keyword within the data, or the volume of followers of an account. Similarly, it is possible to perform powerful regression analysis to predict offline events with social listening data, or to merge with other datasets to understand stock price patterns or whether sales of ice cream are more likely to be impacted by social media campaigns when the sun shines in Toronto.

⁵ https://en.wikipedia.org/wiki/Social_media_measurement
It is also important to note that social listening is an iterative process. Search queries are amended based on the findings of a stage of analysis, for example. Datasets are refined and cleaned, and projects change direction. We might identify a series of online authors through a search for an initial topic, such as COVID-19, and then create a query around these specific authors, agnostic of what they might be discussing, to further investigate our audiences.

**Open-source data**

All social media mentions included in this analysis can be considered ‘open source’, that is, able to be read by the general public. No online mentions behind privacy permissions have been included in the data for this report, be that due to an entire platform or chat being out of the reach of the public, such as a WhatsApp group or a Facebook Messenger discussion, or because an individual account has been restricted, such as a Protected Twitter account. This is also the case for deleted content: where mentions have been removed from online platforms either by the user themselves or the platform, they are no longer available to a social listening platform in their original form.

Open-source data analysis, sometimes known as OSINT (Open-Source Intelligence) is a growing and increasingly important field, made famous in recent years by organisations such as Bellingcat and by companies that straddle the ground between social listing and ‘true OSINT’, such as Graphika. However, the methodology created for this analysis, whilst analysing open-source data for the purposes of intelligence, cannot be considered true OSINT in the same sense. It lacks the forensic fingerprints and painstaking, block-by-block investigations of OSINT. This analysis should be more considered to be an overview of public opinion, where given publicly, around a given subject, and an investigation into how this can be replicated quickly and efficiently in the government sector.

**Open source, off the shelf technologies and their benefits**

In addition to the data itself being open source, we could also consider the technologies and analysis methodologies open source, albeit hidden behind firewalls of dollars and expertise, respectively. An over-arching aspect of this methodology, when designed, was that it could be rebuilt at scale, quickly and relatively cheaply by entities in the government and private sectors. It contains no proprietary technology: these tools can be bought off-the-shelf and used immediately, and require no coding, no internal builds, and no development budgets.

There is also almost no restricted access to data, where it is publicly available: whilst the accuracy and depth of databases varies from social listening tool to tool, only one notable restriction to public social media data access exists – Facebook’s Crowdtangle tool has been restricted to approved companies, non-profits, and academics.

Lastly, there is no barrier in terms of expertise. Social listening tools are easy to use, require only basic setup to begin analysis, and are straightforward to create reports from. In short: easy in, easy out.
Nearly fifteen years after the first social listening technologies were conceived, we largely still exist in a world where communications departments use such technology to understand the number of responses to an Instagram post, but no more; where there is very little overlap in technology or expertise between marketing disciplines and public opinion research. But in many ways, the methodologies, and practices, when adapted to be implemented at scale, are the same. This report aims to demonstrate this fact. And, more importantly, that off-the-shelf tools, already used heavily by private sector companies or communications teams in government, can fulfill the task of analysing sophisticated disinformation campaigns that aim to manipulate public opinion in Canada.

Future applications and redirection of methodology

In addition to the detection and analysis of disinformation, this report aims to demonstrate that such tools and methodologies can be used to understand public opinion at a greater scale. Of course, in analysing how centres of online influence aim to manipulate public opinion and behaviour through disinformation campaigns, this analysis first needs to understand the ‘structure’ of online public opinion on a given subject: in this case, COVID-19. But it needn’t just be COVID-19.

Scalability

Given the sheer scale of public opinion around COVID-19, it is essentially that this analysis forms the start, rather than the end, of such investigations into online manipulation in Canada.

Breadth of coverage

As discussed above, social listening tools collect data that matches the Boolean search query from across the public web. Trillions of webpages have been indexed over the history of the social listening tool, and stored in its database, ready to be accessed by a search query. Twitter data, for example, is available back to the beginning of the Platform’s creation. Similarly, the software collects data in all languages, or in no language at all (slang, emojis etc.). However, to say that a social listening tool, and therefore this study, can access all matching data online would be more than exaggerating.

As a proportion of the available open-source web, it is impossible to guess with any great accuracy how much of it is found in the average social listening tool, but likely far less than one per cent. However, it is likely that any website that has ever been considered ‘missing’ by any user of a social listening tool is found in its database, unless there is a technological, legal, or ethical reason why it shouldn’t be crawled. Data is also ‘cleaned’ within the social listening tool before it matches a search query. For example, the search query written for this analysis was cleaned for pornography, ecommerce, directories, real estate listings and similar categories of website where
public opinion data would likely not be given. However, it is crucial that we look at links to such areas of the web from sites where public opinion is given. For example, if a small community on Twitter linked en masse to a book for sale on amazon.ca, then we need to analyse that book.

**Data availability – Trump**

As mentioned previously, where data has been removed from its source, then it is automatically removed from its host social listening tool. This can take two forms: when an account has removed the post manually, either because the entire account has been removed or an individual post; or when the platform has removed an account or post from its page. This distinction is crucial, and something analysed where possible, in this analysis. When an account has been removed from Twitter, for example, although we can no longer see the original content, we can see where users have linked to an account that has subsequently been removed. We can then see whether that Twitter account has been removed manually (where it will be noted as no longer active – check language) or whether it has been “Suspended” by Twitter.

The most high-profile, and most meaningful to this analysis, instance of such an account suspension was that of former President Trump (@RealDonaldTrump) from Twitter on (date). As laid out, these suspensions meant that Trump’s entire database of past tweets disappeared too. Of course, online archives of Trump tweets exist, where they have been collected manually and sorted in searchable databases. However, in accordance with the terms and conditions of social listening platforms, Twitter data usage, and the ethical considerations of this analysis, such data has not been collected for this report. Despite President Trump being arguably Twitter’s most notable user over the last few years, these tweets have been treated in exactly the same way as the average user who may have deleted their account.

The way that Twitter stores and links its data together has a knock-on effect across the platform. When a user shared content from @RealDonaldTrump in the form of a retweet, Twitter creates a new URL for that retweet, but the content of that tweet is a hyperlink to the original. Therefore, when @RealDonaldTrump was removed, those retweets were essentially removed too. Although this report focusses on Canada, it will outline how political figures in the US form centres of influence in all areas of the political spectrum. Therefore, the analysis has been denied the right to understand fully the impact of President Trump on the Canadian social media landscape around COVID-19. @RealDonaldTrump still features in our online landscape, in the form of, as mentioned above, tweets that have linked to the account, but this should be understood to be a shadow of what might have actually happened in 2020, from the beginning of the pandemic.

**Three stages of data availability in social listening**

Data collected by social listening tools, and therefore for the purposes of this report, falls into three categories.
1. Data that is publicly available and can be accessed by social listening tools. This includes Twitter as its most prominent example, but also online news, forums, and blogs. This data can be accessed by any tool, and sites, such as Twitter, that have strict API restrictions (a limit on the number of times a site can be accessed in a given time period) often have purchasable licenses that guarantee full access to data.

2. Data that is publicly available but cannot be accessed by a social listening tool. This is most often due to a lack of an agreement between a social listening tool and the site itself, meaning that although content might be open to anyone, the site does not allow content to be ‘crawled’ by a platform in the same way that a search engine cannot access it. The most notable example in this category is Facebook, and Facebook-owned platform Instagram. Even Facebook and Instagram pages that are public-facing and can be read manually, are not currently crawled by social listening tools (this relationship has ebbed and flowed over the years).

3. Data that is not able to be crawled by a social listening tool because it is behind privacy settings. This is the case for private pages of public tools, such as Protected accounts on Twitter, Private (PM) or Direct (DM) messages on social media platforms, and for messenger apps such as WhatsApp, Telegram or Discord.

Only data from the first category has been included in this report. Data from the second and third categories may feature in this analysis in another form: hyperlinks. For example, where a public platform is used to share links to a closed platform, we can capture those links. In short, we cannot access the end content for analysis purposes, but we know it is likely to be worth analysing.

This tactic has long been used on social media: nefarious organisations ‘recruiting’ online users to closed channels, where indoctrination and manipulation begin to take hold. Amid suspension of social media accounts, and the near collapse of right-wing social media Gab and Parler in early 2021, following users’ roles in the Storming of the US Capitol on January 6, 2021, many users turned to closed platforms such as Telegram and WhatsApp. Discussions on these areas of the web were therefore more difficult to monitor, but such extremist groups also lost their ability to recruit and advertise for new ‘members’ in the same way they had been doing for years. This report looks closely at such links in the Canadian space around COVID-19, as a means of tracking some of the most dangerous conversations around the issue.

**The importance of taking all relevant data from the public web.**

Arguably the most important question to ask when using a social listening tool is around what to search for. There is a constant balance between supposition and proof: between what we think a social media user might discuss an issue, and how we know they do. Similarly, in data collection terms, there is a constant trade-off between ‘accuracy’ and ‘recall’. The more specific a search query gets, the more we are likely to miss relevant data in the search for only ‘clean’ data. Likewise, the wider we open a query towards how we imagine people
might discuss COVID-19, the more likely it is that irrelevant mentions of “masks” or “jabs” will pervade our analysis dataset.

COVID-19 also provided a unique challenge. Never before in the social media age has a single issue dominated our lives in this way. We might say that almost all public discussion on social media is relevant to the analysis of COVID-19, whether it explicitly mentions the pandemic or not. For example, “I miss going to the movies” is arguably COVID-related, but we can’t say that for sure. The search query therefore reflects this challenge by residing in a half-way house.

In a similar way, we cannot possibly anticipate topics and semantic patterns of posts associated with disinformation narratives. We couldn’t possibly guess even a tiny fraction of the ways people discuss the pandemic, let alone the ways in which influence campaigns seek to lie about the pandemic. The data analysis methodology used by this project reflects this by looking for sharing and clustering patterns in the data, to identify potential areas of disinformation based on anomalies in the network.

Thus, our search query needs to find and collect all mentions of COVID-19 in order to understand the scale, proportion, and nature of the part of the resultant dataset that might be considered disinformation.

3.2 Software

**Brandwatch**

The social listening tool chosen for this analysis project was Brandwatch. Brandwatch can be considered to be one of the leading four or five platforms on the market and works with thousands of clients all over the world.

Brandwatch was chosen for this project for three main reasons:

1. The complexity of its Boolean capabilities: As previously discussed, writing a Boolean search query on the subject of COVID-19 was a difficult proposition. We needed a tool that would support what are known as ‘complex operators’, when writing out Boolean search. In addition to the AND and OR logic statements, used to collect and clean data, operators that define a specific website, geography and language were key. The proprietary Brandwatch operator LiINKS was also required to find mentions that contained links to a website that contained a specific keywork. For example, where someone tweets “I hate this bit.ly/jhhjswijio”, and bit.ly/jhhjswijio links to a canada.ca page about COVID-19 restrictions, then we need to collect that mention, even though it might not say the word “COVID-19” in the tweet.
2. The ability to export large quantities of data from the Brandwatch platform: The millions of social media mentions analysed in this project needed to be exported, either in their entirety for certain aspects of the project, or in a meaningfully large sample. Other platforms permitted only small samples of data for analysis purposes.

3. The structure of the data exported from Brandwatch: This project uses analysis methodologies that can be undertaken with the social listening software, but also bespoke methodologies that require merging of datasets, creation of composite metrics, network analysis and many other processes that have been built to answer the specifics of this project, Therefore, data needs to be exported from the platform in a manageable structure, something that is difficult to do with the inherently unstructured data of social media. Brandwatch data exports are structured in such a way that it somewhat simplified the subsequent stages of the analysis, relatively.

**Gephi**

Gephi is a network analysis (graph theory) and visualisation platform. According to *Wikipedia*⁶, “Gephi has been used in a number of research projects in academia, journalism and elsewhere, for instance in visualizing the global connectivity of New York Times content and examining Twitter network traffic during social unrest along with more traditional network analysis topics. Gephi is widely used within the digital humanities (in history literature, political sciences, etc.), a community where many of its developers are involved.”

Gephi was chosen over other network analysis tools for its ease of use and ability to manage datasets of the size of this project with relative ease. All of the network visualisations contained in this project were built in Gephi.

**Audiense**

Audiense is an audience ‘intelligence’ software that segments universes of social media users based on online ‘affinities’; namely, how people behave online in terms of who they follow, media accounts they consume, brands they show an interest in and other online public connections.

*audiense.com* describes the software thus:

---

⁶ https://en.wikipedia.org/wiki/Gephi
“Audience Intelligence is the capability of understanding audiences based on the analysis of individual and aggregate data about consumers. Audience Intelligence platforms provide insights on the segments or communities that shape that audience, audience psychographics and demographics whilst having the ability to connect audience segments to social listening and analytics platforms, influencer marketing tools, digital advertising platforms and other marketing or consumer research suites.”

Audience was chosen for this research because of its low cost, its ease of use, and fast, exportable visualisations; many of which are included in this report.

In addition to the semantic analysis granted by a social listening platform, social affinities provide analysis of the 90% of social media users that never comment (citation), but follow accounts and consume content, being influenced by what they see. Social affinities segments and categorises audiences based on such patterns, meaning that we can profile members of the Canadian far right, for example, based on the media they consume and the brands they follow, in addition to what they say about COVID-19. We can also derive demographic and behavioural insight from these affinities, which is crucial to reaching such communities.

### 3.3 Graph theory

#### The fundamentals

This project uses graph theory to analyse the primary datasets that are generated by the Brandwatch social listening tool around COVID-19 in Canada.

Wikipedia describes graph theory thus7: “In mathematics, graph theory is the study of graphs, which are mathematical structures used to model pairwise relations between objects. A graph in this context is made up of vertices (also called nodes or points) which are connected by edges (also called links or lines). Graph theory is also widely used in sociology as a way, for example, to measure actors’ prestige or to explore rumor spreading, notably through the use of social network analysis software. Under the umbrella of social networks are many different types of graphs. Acquaintanceship and friendship graphs describe whether people know each other. Influence graphs model whether certain people can influence the behavior of others. Finally, collaboration graphs model whether two people work together in a particular way, such as acting in a movie together.”

Figure 1. An example graph

---

7 [https://en.wikipedia.org/wiki/Graph_theory](https://en.wikipedia.org/wiki/Graph_theory)
Graph theory was chosen for this methodology for the following reasons.

1. Its ability to map large volumes of social media data in one visualisation, showing the main online actors and connections between them.

2. The ease with which it can be read and understood: This is a project that will largely by interpreted by non-analysts.

3. The ease with which anomalies can be identified: The crux of this project is to outline a consistent and scalable methodology for the detection and response to disinformation narratives impacting Canadians. Graph theory, by highlighting anomalies in a graph, underlines where disinformation might be present in a social network.

The social listening and OSINT sectors often favour one, or a combination, of two complementary methodological approaches when it comes to analysing disinformation online. On one hand, software exists that analyses language used online, in the attempt to identify themes and topics of disinformation. Natural Language Processing (NLP) learn as they process millions of online conversations looking for lies and manipulation. In the other camp, we have the approach used by this project: the identification of network anomalies. This project takes the view that machines cannot be relied upon to understand online disinformation at a large scale. Disinformation campaigns, in their most sophisticated form, are not outright lies, but often strategically leveraged truths or exaggerations designed to broaden existing social cleavages (citation). We are not looking for untruths, per se.

Similarly, as discussed previously, social listening requires that we search for something. If we cannot anticipate the narratives of disinformation, then how do we look for them? Analysis of network anomalies looks at strange patterns in how data is shared online. This project uses three hypotheses to underpin its approach: firstly, that social media users are significantly more likely to engage users with whom they broadly agree, and that proportionally little true ‘debate’ exists online. This leads to clustering of users within a social graph. Secondly, that disinformation ‘recruits’ social media users by using public platforms to reach communities of online users, and the way in which this is done is often visually identifiable within a graph due to ‘manipulation’ of the network itself. Thirdly, that the most meaningful analysis of sophisticated themes of disinformation has to be completed by
human analysts, but that far too many conversations are posted online to be read and analysed by human analysts. Therefore, a social graph can be used to point a human analyst to the areas of a network that need to be read manually: filtering the signal of disinformation from the ‘noise’ of everyday social media.

Applications with social media data

Social media is already a social network. We do not have to ‘create’ a social network from scratch from our data. Of course, a certain amount of data manipulation is required to move from the unstructured semantics of Twitter, for example, to a readable network graph, but a lot of the hard work has been done by Twitter itself, in that ‘conversations’ are threaded on the platform: tweets have a ‘source’ and ‘target’.

Therefore, network analysis of social media data has long been an accepted, but still niche, way to analyse social networks. We might argue that most analysis of social media data falls into two camps: segmentation and influence. Segmentation, as topics that are made up of millions of social media mentions can never be described as one conversation. Even within the narrowest of topics, communities exist online based on opinions, micro-topics, geographical or linguistic specificities. Even basic analysis of social media narratives needs to understand the communities therein.

Secondly, influence in an online social network is the ability to change the online, and possible offline, behaviour of a user or part of a network. Understanding influence is the key to running a successful communications campaign or winning an election. Similarly, it is mandatory if we are to understand how negative information flows across a social network. Graph theory excels at both of these tasks, and therefore made it the perfect choice for this analysis project.

Advantages over manual coding/segmentation

Alternatively, ‘coding’ of social media data often relies on subjectivity or whim. There are distinct advantages to the manual analysis of data in many cases, for example when language is technical or sarcastic, or when segmentation is needed along qualitative lines. However, in the case of this project, where we are studying how information travels across a network, via whom, to whom, and how it creates communities of social media users, we need a methodology more consistent and objective. This project uses a graph theory segmentation algorithm known as “Modularity”. Modularity is an iterative process whereby entities in a social network are assigned a community based on common, or strong, connections within the network. In short, an entity has better connectivity with members of its own community, that it does with entities in other communities.
The assigning of an online community is therefore more consistent and accurate, when done at scale, by a modularity algorithm than more subjective methodologies, especially in a project that aims to analyse conversation flow via social media engagement (connections).

Advantages over other influence methodologies

When understanding influence, network analysis also stands out. Within this project, influence should be viewed as not simply the ability to reach the most people with a narrative, but more the ability to reach the most important social media users that are engaged with this topic specifically, to contribute to the formation of online communities on this topic specifically, and to reach other users of influence, also on this topic specifically. We might have a prominent musician with millions of Twitter followers, for example, but is not an authority on the topic of COVID-19 and cannot influence communities on the topic, as almost all of her followers engage only on music content.

Therefore, more traditional metrics to understand influence have not been considered in the majority of this analysis. This includes social media followers, social media engagement (the frequency or likelihood that responses or shares are generated by content), or other ‘scores’ created using composite metrics and subjective analysis. This methodology uses the diagnostics of the graph itself to understand influence: namely, its connectivity. This is only possible using network analysis to understand online conversations.

Variables within a network map – location, botness, age of account, etc., in this case

Network analysis also permits the inclusion of further metrics and categorisation to better understand a network. This report overlays the location of an account, the age of an account and the likelihood of automation, for example, on our social network. This makes it easier to see network anomalies where, for example, a community comprised of automated accounts, posting from one country, is prominent in the graph. In short, a network permits the visualisation of variables outside of the original dataset, which make analysis more meaningful.

Metrics used by this analysis

Betweenness centrality – according to Wikipedia⁸, “In graph theory, betweenness centrality (or "betweenness centrality") is a measure of centrality in a graph based on shortest paths. For every pair of vertices in a connected graph, there exists at least one shortest path between the vertices such that either the number of edges that the path passes through (for unweighted graphs) or the sum of the weights of the edges (for weighted graphs) is

⁸ https://en.wikipedia.org/wiki/Graph_theory
minimized. The betweenness centrality for each vertex is the number of these shortest paths that pass through the vertex.

Betweenness centrality was devised as a general measure of centrality: it applies to a wide range of problems in network theory, including problems related to social networks, biology, transport and scientific cooperation. Although earlier authors have intuitively described centrality as based on betweenness, Freeman (1977) gave the first formal definition of betweenness centrality."

Figure 2. an undirected graph

Two common lay definitions are also used to understand Betweenness centrality. Firstly, if the entities in the network with the highest Betweenness centrality are removed, the network falls apart and ceases to be one network. These entities hold the network together. Secondly, if we draw the shortest path from every entity in a social network to every other entity in the same network, we have to pass more often through the entities with the most Betweenness centrality. In short, these are our gatekeepers or social liaisons, and our most influential nodes in a communication graph.

Botness – A range of metrics have been created to understand the extent to which an online entity might be automated. Like many metrics associated with social media analysis, our understanding of automation becomes
more accurate the larger the sample size. At a macro level, a formula can afford to wrongly categorise individual accounts, for example, but at the level of thousands of accounts, we can rely more so on that metric.

For the purposes of simplicity, a basic formula has been used to understand automation in this analysis. Twitter accounts that have historically posted more than 50 times each day that they have been active, and are not Verified by Twitter (blue tick) have been categorised as automated. The non-Verified step removes the chance that media or brand social media accounts are categorised as automated.

In terms of analysing automation, this is quick but effective approximation. In reality, accounts behave in increasingly strange ways to outmanoeuvre detection of automation, and ultimately removal from a social media platform. This includes lying dormant for months or even years after creation, then posting a burst of content suddenly, for example, or consistently changing its user handle, content topics or accounts that it engages. All of these are difficult to detect automatically and therefore could not be included in this analysis.

Account age – Account age is simply the number of days that an account has been active on a social network. Although accounts that have been more-recently created, created seemingly in batches, or created to coincide with an event or an uptick in disinformation, might be the subject of further scrutiny, they are not automatically designated as suspicious.

K-core – This is a simple but crucial metric used in the creation of the networks in this analysis. For reasons of aesthetics, computing power and more accurate understanding of influence, only the ‘core’ of our social networks has been visualised and analysed in this report.

The main Twitter network in this analysis visualises and analyses 34,711 online entities, and 173,968 connections between them, from a total dataset of nearly two million unique Twitter accounts, posting more than 41 million times in the reporting period. These are the nearly 35 thousand most important entities, based on two factors, and therefore our graph can be understood to show the most important ‘sample’ of the graph.

- Entities were selected for inclusion in the network only if they are both a ‘source’ and a ‘target’ in the dataset. In short, if they have both created content on COVID-19 in Canada that was subsequently engaged by other users and engaged other users on the topic themselves. We might view this as an abbreviated form of the eventual understanding of influence. Entities with high Betweenness centrality need to be bridges in a network, and can only form these bridges if they are both source and target. If an entity does not do both of these things, we can exclude them from our network graph.

- Entities needed to have generated a minimum number (check) of engagements when posting content on COVID-19 in Canada. Therefore, the methodology excludes entities that push out tweets, for example, that don’t influence the conversation.
The implementation of these filters took our original dataset of nearly two million entities down to the 34 thousand that were eventually graphed. Accordingly, all metrics that were subsequently calculated, were calculated using the network core. Segmentation was therefore applied to only the most important entities in the network, and influence was calculated using Betweenness centrality on the core of the network. Or, in lay terms, influence is understood based on an entity’s ability to influence other influencers.

The five advantages of graph theory/when analysing social media data

We can point to five conceptual advantages when using graph theory to analyse social media data, in addition to those outlined above.

Specificity – the Boolean search query allows us to be incredibly specific in terms of what we subsequently visualise and analyse with the network. The query defines semantic keywords and patterns, geography, and site. However, the network methodology also helps to clean data and to showcase the most-relevant elements of the conversation. For example, the K-core filtration discussed previously makes it difficult for an entity contributing irrelevant data to enter our resultant analysis dataset. Or, when irrelevant data does slip through the cracks, it becomes clear, when the network is visualised, that this topic does not belong in the final network, due to a lack of connectivity, for example.

Similarly, because of the specification that an entity needs to be both a source and a target to ‘qualify’ for the network, and to accrue a meaningful Betweenness centrality score, only entities that can be a source (i.e., an original poster, meeting the search query) can be considered important by the network. These are complex ideas, but, in short, the network and the way it has been created, is self-policing in terms of ensuring irrelevant data is analysed.

Filtration – Filtration is a benefit in a few ways. Firstly, the previously discussed ways in which the data is filtered before it is visualised means that the metrics that are derived from the network are stronger. Secondly, the visualisation itself is easier to read and process, as it only includes the most meaningful aspects of the network. And thirdly, the network itself can be filtered to show an individual community within, or possibly even one entity and its connections, making visualisation and analysis significantly easier. Simply put, if we need to quickly understand the importance of 10 accounts from a dataset of everyone discussing COVID-19 in Canada in a 10-month period, then this is a straightforward process.

Segmentation – As discussed previously, this is the process of segmentation of vast datasets based on common connections, rather than subjective or NLP-based methodologies. It can also be implemented across multiple ‘dimensions’ simultaneously. For example, including metadata of an account, such as geography, language, or age, when segmenting a network.
Visualisation – Visualisation is crucial to network analysis in two ways. Firstly, the visualisation of a network is often aesthetically appealing and alluring for analysts and non-analysts. It turns what can be mundane analysis into something that grabs attention. Secondly, it is easy to read for lay people. With a basic explanation, people with no experience of social media data, or even data, can understand broadly what might be happening in a network visualisation. This ‘democratises’ the process of analysis of disinformation, taking reports out of the hands of specialists to towards decision-makers.

Quantification – Every aspect of a network graph is quantified. The location of every node, the distance between them, the size and shape and colour of each node, even the curvature of each edge (connection) is not an accident. We might accurately say that an entity’s Betweenness centrality, and therefore its influence, is 9.43x greater that another, given the way that metric is calculated. Networks are consistent and can be set-up for cross-comparison. Network-derived data can also be used to create composite metrics outside of the network, for example.

3.4 The simplified graph theory process

To better understand how a network graph is built, and its fundamental principles, this section of the report walks the reader through this process. In addition to clarifying the eventual analysis in this report, the outline also seeks to clarify, or remind of, the basics involved in online (or even offline) communication. Disinformation, or influence campaigns in general, are often looked at as strange phenomena, manipulating the online world to influence public opinion, but in truth, those that seek to manipulate often profoundly understand the principal of connectivity, networks and how information travels.
Figure 3. An example of a two-person network

The visualisation above shows the most basic form of social network. Two people, with a mutually strong relationship. Information passes in both directions in this relationship. These networks are the most significant when we discuss online influence. It could be argued that the aim of every online campaign, good or bad, is to influence an individual person via another: to recreate the organic conversations between two people in the online world, where one person trusts another. It is the same with disinformation. Bad actors seek to establish trust and intimacy through a variety of methods. Every social network is made of these building blocks.

Figure 4. An example of a three-person network

Figure 4 above shows the natural progression of this network: three entities with manually strong relationships, each connected to each other.
Figure 5. An example of a larger social network

Figure 5 above shows a larger social network, and one that is beginning to look more like our end network graph. D is the most important element of this network, with the most Betweenness centrality, and therefore influence, by the metrics in this report. Communication always needs to travel through entity D to cross the network fully, making D a gatekeeper, or influencer.

Figure 6. An example of a weighted social network

The visualisation above (figure 6) shows one of the edges variables we have added to the network. Here, a ‘stronger’ relationship is shown by a heavier edge (connection) between C and B. This is due to more frequent communication between these entities in the network. We can state that C and B communicate more often, on our topic, than A and B, for example.
Figure 7. An example of a proximity-weighted social network

Strength of relationship in the form of edge weights is also reflected in the visualisation, in terms of proximity of entities. Entities naturally cluster into communities based on common connections, whilst two or more entities that share strong connections will gravitate towards each other in the network layout, for ease of reading.

Figure 8. An example of a social network showing influence

Size of nodes denotes Betweenness Centrality, or influence. Larger nodes in the network are traversed more often when we draw the shortest path between all combinations of nodes. In figure 8 above, entity D is the most influential, and therefore largest node.
Modules, or communities, in the network, are colour-coded for identification purposes. Network entities share more, and stronger, connections with members of their own module than entities in other modules. Figure 9 above shows this.

Figure 10 above shows a further progression of this network, with more nodes and edges, but exactly the same set of metrics, colour, and size denotation. This is a network of multiple sclerosis doctors in the United States. This network clearly shows where influence sits in small networks.
Finally, figure 11 above shows a larger network still. This is a network of people in the United Kingdom discussing the issue of refugees in Europe. As previously, the metrics, colour-coding, node sizing and edge weighting principals remain the same. The network provides an excellent representation of how networks can be used to understand structure and polarisation (both of which can be expressed quantitatively). Visually, two poles in the network exist: to the right, social media accounts that are against refugees coming to Europe; and, to the left, communities that are largely sympathetic to the plight of refugees. The polarisation of this network is profound, with little genuine discussion or even debate between opposing sides. This is, of course, likely to have been reinforced by social media algorithms, ‘filter bubbles’, and an ‘echo chamber’ mentality. Each of these elements are worth exploring further outside of this report, but we need to understand at this stage that they contribute to the formation of discreet communities online, at least in addition to organic preferences.
3.5 The graph explained

Figure 12. The master Twitter network used for this report

The visualisation above (figure 12) is the main social network used for the analysis in this report, displayed to show a natural progression to an even larger network: this time with tens of thousands of nodes and hundreds of thousands of edges between them.
Figure 13 above shows an enlarged image of the centre of the network, in order to show more closely the individual nodes and how they cluster. The centre of each social network map, due to the way networks are formed and communities meet, mostly tend to show what we might call the ‘mainstream’: in this case, the green community in the centre is formed of Canadian Federal Government accounts and mainstream national media.

3.6 The search query

This section of the report details the process that begins the methodology – the Boolean search query. As disused previously, Boolean logic is a series, of possibly hundreds of thousands, of logic gates that both collect and reject (clean) social media mentions that match the search. This functions in a similar way to an advanced Google search, although with the ability to ‘nest’ searches (creating multiple different searches within one) and for a search to run into the tens of thousands of characters – although this varies by software provider.

Boolean logic explained – Brandwatch-specific operators

The most basic ‘operators’ used by Boolean are AND, OR and NOT: used to insist that multiple keywords are used together, that either keyword can be used, and that a specific keyword cannot be used, respectively. These three operators form the crux of the search query that was eventually used to collect our social listening data. However, dozens of advanced Boolean operators are available with social listening software – these are
crucial to refining the data, and collecting only relevant mentions for our analysis. The advanced operators that were used in this project are listed below:

<table>
<thead>
<tr>
<th>Operator</th>
<th>Description</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEAR/x</td>
<td>Will find mentions of 'covid' within 5 words of 'ontario' or 'quebec', and mentions of 'corona' within 5 words of 'ontario' or 'quebec'.</td>
<td>NEAR/5 (covid OR corona) NEAR/5 (ontario OR quebec)</td>
</tr>
<tr>
<td>country:</td>
<td>Will only find mentions of the exact phrase 'covid 19' that have been identified as from Canada.</td>
<td>country:can AND &quot;covid 19&quot;</td>
</tr>
<tr>
<td>title:</td>
<td>Will find any mentions where 'covid in canada' appears in the page title.</td>
<td>title:&quot;covid in canada&quot;</td>
</tr>
<tr>
<td>links:</td>
<td>Will find Mentions containing links to all URLs containing 'covid', including expanded short URLs. Note: in this case, if the links: operator had not been used, Mentions containing shortened links to a URL containing 'covid' would not have been picked up.</td>
<td>links:covid</td>
</tr>
<tr>
<td>Wildcard *</td>
<td>Will find mentions with the root word 'covid', e.g., 'covid', 'covid19', 'covid-19' etc.</td>
<td>covid*</td>
</tr>
</tbody>
</table>

**Sources, languages, etc.**

The process of building a search query relevant to the topic of COVID-19 in Canada is not straightforward, for a variety of reasons.

1. Although many social media users do use the keywords, or variations of the keywords, “COVID-19”, “Coronavirus” etc. when discussing the pandemic, we cannot guarantee that this is the case. People may equally use “pandemic”, “anti-mask” or derogatory terms such as “China virus”. Our search needed to be wide enough to include as many relevant mentions as possible, without including irrelevant mentions that would skew our final dataset.

2. Social media users based in Canada often do not display that they are based in Canada, or when they do, social listening software might not pick up on this. A small percentage of social media users post locations or coordinates when contributing publicly. A larger proportion ‘gives’ their location in a social media profile, but this still amounts to less than half of data we suspect might be generated by Canadians. Lastly, giving
one’s location as “London” could be London, ON, but we have no way to confirm that absolutely, in an automated way.

3. Social media users based outside of Canada are able to influence the discussion. Social media is borderless, and conversations are far more likely to align themselves linguistically than geographically, especially on genuinely global subject matters such as COVID-19. Therefore, we need to capture as much of this information as possible, also.

Therefore, the following stipulations were made on our search query.

I. The search query would include a long list of words associated with the pandemic, all keyword variations and known slang around the virus, and links to content about the virus. Similarly, the search would contain all mentions of keywords that are, anecdotally at least, suspected to be almost-always linked to the virus in our data collection period, such as “anti-mask”. Likewise, the search would not include all mentions of the keyword “mask”, as it was considered too general.

II. The search would collect all data posted by social media accounts confirmed as being based in Canada, and all mentions that match our keyword criteria alongside Canada-specific keywords and hashtags. This would include a list of country, province and city names, political figures, and common Canadian hashtags.

III. If a user is based outside Canada and attempting to influence the discussion in Canada, specifically, we should assume that they would use Canada-specific keywords. Therefore, this data would be captured at a global scale.

The query building process – iterations

The creation of a social media search contains an inherent problem: how do we search for something we don’t know exists? Or, to put it another way: we might be able to anticipate keywords that collect data we know will be there (for example “COVID”), but this will inevitably miss a large chunk of social media mentions about COVID-19 that don’t use specifically that keyword, and that we hadn’t anticipated.

The search query was therefore constructed in two iterations.

1. Firstly, keywords we know were added to the search, simply through brainstorming among the team, and additional desk research using Google. These included “COVID” and variations, “coronavirus” and variations, general terms such as “the pandemic”, abbreviated terms such as “C-19” and slang and derogatory terms, such as “convid” or “scamdemic”.
2. Next, this search was created in Brandwatch, and the data was analysed. The most common search terms were extracted and added to the search. These keywords fell into six categories: locations, organizations, people, general keywords, phrases, and hashtags. Where these keywords were used more than six thousand times during our reporting period, they were taken aside. Next, they were segmented into the following categories.

- Unambiguously Canadian COVID-related - standalone terms - e.g., "#covid19canada"
- Unambiguously COVID-related - requires Canadian geography or context - e.g., "#covid19"
- Not always COVID-related, but we can make the jump that in the period studied, the terms will nearly always relate to COVID - requires Canadian geography or context & exclusion terms where relevant - e.g., "#wearamask"
- COVID-related with context only - requires Canadian geography or context, COVID context & exclusion terms where relevant - e.g., "vaccine"
- Unambiguously Canada-related - for clarifying Canadian context - e.g., "#cdnpol"
- Not directly related - incidental and not part of the search query

3. Keywords germane to the top five categories listed above were then added to the search query, with the relevant context: for example, "#covid19canada" required no context, while "#wearamask" required the context of one of the terms with "Canadian geography or context". The latter category itself was also built out using these discovered keywords, adding, for example "#cdnpol" OR "qcpol".

4. This process was undertaken for the English and French languages, using native speaking analysts. Keywords that are not language-specific, such as “COVID” were sources in all languages. Or, more relevantly, no languages – with, simply put, the pattern of those characters identified, rather than the language of the surrounding text. This also included slang, emoji-rich text and other character combinations that might not constitute a known ‘language’. Despite this, more than 96% of the data was classified as either English or French, with much of the remaining 4% also likely to be in these languages, but simply unclassified by the social listening software.

Accuracy versus recall. Diminishing returns.

It is also worth noting at this stage that query creation, especially when an iterative process, ascribes to two sliding scales.

Firstly, ‘accuracy versus recall’: as noted previously, the more ‘accurate’ we strive to make our search, the more mentions we could possibly miss. Likewise, the more open our search to wide variations of how people discuss COVID-19, the less relevant the final dataset stands to be. It’s a balance and, for the purposes of this project, one weighted towards accuracy.
Secondly, we quickly hit diminishing returns when creating a search query. To use the process outlined above, keywords we know are likely to contribute a large share of our eventual dataset. Or, looked at another way, we could collect 80% of our data in the first 20% of the time spent writing our search. In this project, for example, 62% of the data collected for this report was captured simply using the terms “COVID” and “Corona”. Despite this fact, it is crucial to include those wider search terms. We need to represent and analyze all groups of people discussing the pandemic. If they use different words for linguistic reasons, socioeconomic or educational reasons, social media syntax reasons or reasons of online ‘cultures’, we need to include them.

3.7 Final query

After each of these considerations, the final search query was created. It is shown below, with the same syntax as discussed previously.
The result was a search query that aimed to recreate how people speak about the pandemic online, but not to overreach into the realms of irrelevance. Of course, there are millions of conversations relevant to the subject that remain impossible to capture. On the disinformation front, a phrase such as "this has all been created by China to damage the West" will, simply, never be collected by a search query. This, of course, doesn't begin to cover the infinite ways that people can post online without using words at all.

3.8 Data gathering

The Brandwatch tool was then used to collect and store the data. Nearly 53 million social media mentions were found during the period March 1 to December 31, 2020.

This period was chosen to begin as COVID-19 began to travel outside of Asia for the first time and, more importantly, when social media users started to discuss the issue. For example, despite COVID-19, or "Coronavirus" as it was generically known then, being present in China from December 2019, less than 4% of our eventual dataset was discovered prior to March 1, 2020. These mentions have been included in some temporal analysis in this report, but the data has not been included in the network analysis.

Networks

The data was segmented at this stage into the following categories for reasons of data manipulation and to reflect how social media is used: into a Twitter and a non-Twitter network. Twitter is largely a self-contained social network. Whilst links to websites and other social media away from Twitter are found in a high proportion of tweets, they are largely secondary to the account-to-account ‘engagement’ of the Twitter platform. Twitter also, due to re-seller agreements with social listening platforms, and the largely public nature of Twitter (only a very small percentage of all users have Protected accounts), contributed the vast majority of our dataset (77%).

Of course, the same could apply to Facebook, Instagram, and other high-profile social networks, but as previously discussed, the data from these sites is far less available to social listening providers, or even proprietary tools, than that of Twitter.

The non-Twitter network contains everything else that was able to be scraped by our search query, and the links away from these sites.

Twitter social network
The Twitter network created for this analysis comprised the most influential 34,711 online entities (nodes) that either matched the search query during the reporting period or influenced conversations that matched our search query in the reporting period. The “most influential” were defined using the K-core filtration method, outlined on page 24). These nodes were connected by 173,968 edges. Edges between Twitter users were mapped where direct engagement had occurred on the issue of COVID-19 in Canada in the reporting period. Engagement may take the form of a ‘threaded conversation’, shared content (retweets) or links to another account or content posted by another account (known as quoted tweets, images, or video).

Links away from Twitter were also mapped. When a Twitter user contributes a view on the pandemic and links to a news site, other social media, or even areas of disinformation, we need to understand those connections too. Therefore, the Twitter network visualization includes a variety of sites.

**Web network**

The ‘web network’ (the *everything else* network) comprised the most influential 25,241 online non-Twitter entities, connected by 32,231 edges. Edges were formed by hyperlinks between websites. For example, where one site links to another either in the body of the text itself, or immediately surrounding the news article, blog post, Reddit subreddit or any other webpage. All hyperlinks were found on webpages that matched our search query.

Both webpages that matched the query and influential links away from these pages were mapped. Again, we used the K-core method to filter for the most-linked pages. Similarly, data cleaning process was crucial at this point, with pages often linking to ads, commercial sites, and other dead areas of the web. Pages were also segmented into social media and non-social media. The definition of ‘social media’ was extended at this stage to sites where users have an individual profile that constitutes a main way in which a site is navigated. We might understand, for example, a Twitter account to be an ‘individual profile’, while a Reddit user is not, as the ‘currency’ of Reddit is the subreddit. This distinction, of course, was largely subjective, but crucial to the creation of the network.


The resultant network visualization segmented across two main dimensions: site type, and viewpoint. For example, Tumblr profiles were highly likely to link to other Tumblr profiles, in addition to news sites that match a specific opinion.
3.9 Data integrity

The data integrity considerations associated with the social listening sector, and analysis of open-source communications, in general is complex. Sensitivities are both legal and ethical in nature, whilst ‘legitimate interest’ claims are also germane to how data can and must be processed.

The European Union’s 2018 GDPR legislation, despite providing legal guidelines to only the 27 member states of EU, also revised thoughts on the responsibilities of data collecting methodologies, data processing analysis companies, and the issue of personally identifiable information (PII) and consent in the digital world. GDPR arguably raised the bar globally in terms of how data is processed and stored by digital companies, and social listening tools and research methodologies have reflected this in the last three years.

Regardless of the legislation in Canada, the global nature of the data processed in this report, and the myriad locations of the root data sources (websites) mandates that, from a legal perspective, we abide by the strictest global data processing laws, where possible within the objectives of the project.

To address these issues one-by-one:

Data collection – As previously stated, all data in this report is found on the open-source web. It has, therefore, either through opt-in or opt-out permissions, been ‘published’ by its creator, either on social media platforms using user visibility permissions, or other public websites. No data from closed sources, private messaging or non-crawlable sites has been included.

Data processing & inferences – In the analysis of data for this project, only semantic and visual content was analysed, and connections between users. In short, only data that was published by the user in the public domain. No data was further processed to make inferences about individual social media users in terms of their political leanings, sexuality, gender, race, or religion. Inferences were made about political leanings in the aggregate, as per the objectives of the research. Where data was merged with secondary data to ‘enrich’ profiles, this was also done in the aggregate only, and only with open-source datasets.

Data storage – For analysis purposes, Brandwatch and Microsoft Excel stored ‘copies’ of our source data, either in the form of ‘images’ of social media content, or in the form of raw text database entries, such as the text of the tweet. This data will be deleted on completion of the project, from both sources. Links to original accounts and posts will remain in the written documents, and images of social media posts will remain in the analysis, but both databases will be deleted.

Consent - This project will use certified social media monitoring software that has in-built protection via their relationships with the primary data providers: Twitter, Facebook (including Instagram), Reddit et al; plus, all
open websites and forums that permit data collection. With each of these platforms, users must consent to ‘publish’ their data, and also to make it accessible to third party data providers such as social listening platforms.

Personally identifiable information (PII) – All PII included in the datasets analysed in this report has been voluntarily published by its owners. To the knowledge of this project, no social media platforms that were analysed mandate the publication of PII as a pre-requisite for usage, and privacy controls and data permissions are freely able to be changed on these platforms. By implication therefore, where PII is available to analysts, it has been given, unsolicited, by its owner.

However, given that this is a project commissioned and funded by a government entity, and involving the analysis of such a vast topic, it is crucial that this project goes beyond its legal requirements. For example, we might argue that if this project were commissioned by Nike, or a similar brand, and the company wanted to understand who was talking about Nike, then we could make the ‘legitimate interest’ argument that Nike deserves to know who might be talking about the brand publicly. However, this project analyses, by design, the general public, and public opinion about one of the most significant events many people will have lived through. We need to be extra careful in terms of data in processed and analysed and even more sensitive concerning publication. Therefore, a distinction has been made between these stages of the process.

Whilst each of the issues addressed in this section of the report remain true from the analysis stages of the project, far tighter data protections have been applied to the publication.

Ethically, even where content is posted by social media users with full consent and where social networks allow for data collection, this project does not report on the activities, opinions or location of any ‘regular’ social media user. It is necessary to analyze, in an aggregated, anonymized way, these users to understand the spread of disinformation and their exposure to such narratives, and therefore information about these social media users (albeit only information that is publicly available) will be accessible to researchers involved in this project. Similarly, it is necessary to make inferences about these users, in terms of how opinions, political leanings and exposure to centers of influence inform community membership, but identifiable information about these users will not be published, either PII or content that would allow for the tracing of these individuals (such as verbatim, unaltered content example).

An exception to this rule will be applied where social media users give reason to believe that they are an automated account (a bot), an organizational account (including private companies or public entities) or a self-identified publisher (defined as an individual that deliberately tries to influence an online narrative through published content in news media, a blog, a forum or social media) such as a journalist, blogger or social media ‘influencer’.
4.0 Network analysis

4.1 The Twitter network

*Figure 14. The master Twitter network*

The visualization above (figure 14) is the final Twitter network. The methodology is discussed in full in that chapter of this document, in brief, 34,711 online entities (nodes) are visualised, with 173,968 connections (edges) between them. The size of the node denotes the extent to which that entity is considered to be influential within the network, based on the bridges they create between other entities. Colours indicate clusters, also referred to as
“communities” or “neighbourhoods” in this section of the report. Clusters are defined by the extent to which a node shares common, and strong, connections with other members of its community.

Based on the identities of nodes, the content that they post, media they consume and connections within the network, these communities have been labelled. These labels carry a natural margin of error: community membership is not entirely consistent with political allegiance, for example, or geographic elements. Membership is defined algorithmically according to the extent to which an entity engages with other members of that cluster. If, for example, a dedicated, self-proclaimed Liberal supporter spends the majority of her time on public social media responding to content posted by members of the far-right community, then that Liberal supporter will be found in the Far-right cluster of the network. Of course, segmenting network in this way relies on the qualified assumption that social media users, and possibly humans in general, spend the majority of their time online engaging people with whom they agree. This is especially important on social media given the importance of online ‘identity’. Therefore, whilst outliers exist within each cluster of the network, a large majority, after human verification, ‘belong’ in these clusters.

One significant exception to this ‘rule’ covers how, and which, media is shared. Social media users are highly likely to share media with which they agree, due to the fact they have read it initially, broadly support such publications’ views, and like to ‘be seen’ as sharing such content, again as an identity-builder. However, this is not always the case. Social media users, especially on the right of politics and even in disinformation circles, often share articles with whom they often disagree in order to further prove a point: if even our political enemy admits something, it must be true! This leads to what might be considered anomalous network cluster membership on occasion, but not enough to skew the efficacy of even basic reductive labelling.

4.2 Communities

Seven distinct communities are visible in the network, with other smaller neighbourhoods visible on the fringes, often comprising of specific media outlets, for example. More than four-fifths (83%) of the Twitter entities in the network fell into these seven clusters, whilst 69% of all entities were categorised accordingly. This discrepancy is largely due to a large number of media articles having no distinct ‘home’ in the network, being shared by only a small number of accounts. A ‘media entity’ is a URL shared by these Twitter accounts, and can be found across the public, and even private (see methodology chapter) web, on news, blog, forum, video or image sites, or other social media or chat platforms.
The main communities have been defined according to the segmentation and labelling shown on figure 15 above. Three main factors contribute to the overall segmentation of the network.

**Figure 16. Mentioned of COVID-19 by network cluster**
Firstly, Political persuasion is crucial when social media users discuss COVID-19 in Canada, in terms of everything from practical government COVID-19 responses to deeper questions linked to tangential parts of society, such as attitudes towards immigration or LGBTQI Canadians. Perhaps unsurprisingly, given the nature of the Canadian federal political party system, where politics is the most important and most defining element of the community, it breaks into two: what has been labelled Right-Wing and Progressive communities. This is separated from Government not in terms of political stance, but by the nature of the content posted by these entities. The Government cluster might be seen as largely administrative, linking to federal information pages, COVID-19 restriction updates, travel information and ministerial Twitter accounts. Government is the only cluster, other than Québécois and the Right-Wing, where cbc.ca was the most shared website, with canada.ca being more popular.

Secondly, geography is a huge contributor to network segmentation. COVID-19 response has largely been administered at a provincial level. Restrictions and mandates are mostly locally imposed and epidemiologists and virologists have worked closely with provincial health ministers and chief medical officers, with the latter often being the most prominent face the pandemic. In short, we shouldn’t be surprised that social media users are sometimes more likely to discuss local issues, and to cluster accordingly, almost regardless of political persuasion.

Lastly, there are linguistic lines across the network. Of course, the social media content we captured for this report is semantic, and therefore members of the surrounding debate need to speak its language. This might sound profoundly obvious, but it is less often the case with image or video social media content, nor with other areas of online discussion, such as celebrity news, where short quips, hashtags and emojis are employed and a fluency of language is less of a barrier than within a complex topic such as COVID-19.

Therefore, is should be expected that a distinct Québécois cluster has been identified, outside of the core of the network. This label has been chosen according to the main language or discussion and the main subject matters of the cluster, rather than a specific geographical analysis. Unlike with the British Columbia or Alberta clusters, the defining feature of the Québécois cluster is not the province itself: at least not overtly; it may be implied that by speaking about general subjects that pertain to COVID-19 in Canada, in the French language, the social media user at least has the context of Québec or New Brunswick in mind, but that inference would be largely subjective.

The location of the clusters themselves, particularly in relation to the Government core of the network is also interesting. Due, in part, to the overlap with the current ruling Liberal Party, the Progressive cluster is far closer to the Government cluster than any other. This is also due to qualitative reasons. In short, members of the Progressive cluster are more likely to engage those in the Government cluster because they are closer to their views, share the same media, and see a common approach to COVID-19 measures. This, of course, is where analysis of the online network bleeds into wider societal segmentation, with liberal, outward-looking, arguably more likely to share commonalities in ‘outlook’ with governments, particularly in many Western democracies. This might be on a policy level, for example in terms of views on the economy or LGBTQI Canadians, or broader
attitudes towards ‘official’ media sources. A combination of all of these factors explains the closer proximity of Government and Progressive neighbourhoods.

4.3 Segmentation branches

For the purposes of this analysis, the three identified primary reasons for network segmentation only get us some of the way to understanding areas of the network where disinformation might be more prevalent. Clusters that were formed based on political persuasion could be further sub-divided based on the ‘wing’ of that persuasion inhabited by the Twitter entity, or by how the specific entity behaves on social media. In short, these communities are formed by a political ideology within which a spectrum of views exists. By filtering the network and reapplying the same modularity algorithm, we were further able to segment Progressive and Right-Wing neighbourhoods of the network.

Figure 17 shows the second segmentation iteration of the Progressive cluster.

Figure 17. The Progressive cluster further segmented

As is clear from the colour-classification, none of the 14 newly identified communities inhabit one distinct area of our original network cluster. The new clusters overlap each other and largely reside in the same area of the map. This could be simply because of different conversations within the COVID-19 conversation, or due to slightly different organisations or bodies being present in the discussion. Due to this largely homogenous analysis, it was therefore decided to keep the Progressive cluster as one community for further analysis and comparison.
Alternatively, the Right-Wing cluster fractured into three clearly defined sub-clusters, shown in figure 18.

Two of the three sub-clusters represented what we might consider the poles of Canadian right-wing politics. The Anti-Liberal sub-cluster largely defined itself through its Conservative Party of Canada membership (including leader Erin O’Toole - @erinotoole), its opposition to the Prime Minister and the government Liberal Party of Canada, but its broadly mainstream conservative views towards COVID-19: providing opposition, but largely in agreement with the tenets of international response. The Far-Right sub-cluster, alternatively, is the home of much more extreme views, conspiracy theory, international influence and sharing of radical publications and videos. In addition to many bots and extreme accounts, we find Maxime Bernier (@MaximeBernier) leader of the People’s Party of Canada. Lastly, in the centre of the cluster, we find a smaller sub-cluster dedicated to fellowship of the publication Rebel News and its founder Ezra Levant.

Due to the nature of this sub-division with the Right-Wing cluster, and the nature of the political conversation therein, it was therefore decided to continue with these three subdivisions for the remainder of the analysis, with direct comparisons to other clusters in the network.
4.4 Language

*Figure 19. Language per network entity*

In figure 19, the network has been recolored according to the primary language of each entity. Entities were classified based on the language used to post the largest share of their content on the topic of COVID-19 in the item period. So, for example, if an entity largely posts about Hockey in English, but mostly uses French to discuss COVID-19 then they are considered French for this analysis. English-language entities are coloured Green; French-language entities are orange, whilst other languages are present in very small quantities (just 20 entities in the network were Spanish-language, for example). As expected, the pattern of French-language entities largely overlaps with the *Québécois* cluster, with one small exception. Figure 20 shows the breakdown per network cluster (‘Other’ includes unclassified entities).
Language of entities discussing COVID-19 in Canada
Segmented by network community

Site Type

Figure 21. Site type per network entity
Figure 21 above shows the distribution of site types across the network. More than half (57%) were classified as 'Media': news sites, primarily. These web pages were linked-to by Twitter accounts within content about COVID-19. 'Media' with few, if any, links to the centre of the network, or even disparate clusters, congregate around the edges of the map, and are shown in brown. The most influential media entities in the network are almost all Canadian national media, or Government sites. This is the case in most clusters, with the exception of the political fringes. Figure 22 below shows how this varies across our network clusters, with all non-Twitter sites merged for simplicity, since ‘media’ and Twitter contributed a combined 98.67% of the network. Interestingly, clusters under the Right-Wing banner were proportionally slightly less likely to share media content.

Figure 22. Site type distribution per network cluster

**Total mentions of COVID-19 in Canada**
Segmented by network community; segmented by site type
4.5 Country distribution

Figure 23. Country per network entity

Figure 23 above shows the country of origin of each entity in the network. As for language, the location of each tweet posted by all entities was analysed, and an overall location determined based on the country of the largest share of tweets. Therefore, an entity might have left Canada and continued to tweet about COVID-19 in Canada, but the majority of her tweets were posted in Toronto and therefore she has been classified as Canadian.

The overwhelming majority of all tweets that discussed COVID-19 in Canada were posted domestically, with the exception of three of the identified ‘political’ clusters in the network. Figure 24 below shows the breakdown by cluster.

Figure 24. Country distribution per network cluster – all sites
The location of Twitter accounts is determined based on a hierarchical process. If a Twitter user makes her GPS coordinates available at the point of tweeting, then this is the location designated. However, this is only true for a very small proportion of all tweets (thought to be less than one per cent). Therefore, the next step is to look at the given location of the Twitter account, whether at a city, region or country-level. This given location is then verified by both time zone and language to disambiguate locations of the same name. For example, if a user gives their location as 'London', but has a time zone of EST, then we can make the assumption that she is in Ontario. Anything that doesn’t fall into this category defaults to the server address of the site itself – in the case of Twitter, the United States. Twitter users that do not give their location for whatever reason are automatically classified as US-based, creating a skew in the data. It is therefore crucial that we view the chart above in three ways: firstly, by only comparing proportions across clusters, rather than simply looking at absolute numbers; secondly, by understanding that Twitter users in ‘other’ might be based in Canada but for a variety of reasons do not give a location; and lastly, that whether a location is given has also impacted our ability to capture COVID-19 data in the first place, of course. If, for example, there is an aspect of the Right-Wing Twitter identity that dissuades giving a location for whatever reason, then that network cluster might be underrepresented more generally.

The location of non-Twitter links was assessed based on the IP address of the domain’s server. For sites such as YouTube, all posts ‘default’ to the United States due lack of precise user location data. Therefore, due to the volume of media servers originating in the United States, even when carrying directly Canadian information, we should perhaps expect this skew towards non-Canadian sites.
As mentioned previously, when we look at Twitter accounts specifically, due to the fact they represent the people in the debate rather than the media, entities in the Progressive, Rebel News, and Right-Wing clusters (three of the four ‘political’ clusters) are far less likely to be based in Canada.
4.6 Provincial distribution

Figure 26. Province per network entity

Figure 26 overhead shows the breakdown of the network by province. Provincial classifications were undertaken using the same methodology as for countries: the majority of content posted on COVID-19 by that author in the reporting period. Only Canadian provincial breakdown is shown within the map: non-Canadian geography in simply classified as “Outside Canada”.

More than one-fifth (20.96%) of all entities in the network are Ontario-based. Québec provided 7.96% of the network, broadly the same as the Québécois cluster in size. Figure 27 below shows the provincial breakdown per cluster, further helping to explain the geographical labels of some of the clusters in the network. The Government cluster was the most evenly distributed across Canada, as perhaps should be expected. Entities situated in Newfoundland, Nova Scotia, Nunavut and Prince Edward Island all over-indexed in this neighbourhood of the map.
The visualisation shown as figure 28 shows the extent to which each province over or under-indexes, compared to its population, within each political cluster, with Government shown as a control. We clearly see that Albertans hugely over-index in the Anti-Liberal and Rebel News clusters, by 13.28 and 11.68 percentage points respectively. The inverse is true with the British Columbia cluster, with social media users in BC far less likely to contribute towards these networks than might the case given the province’s population. Ontarians over-index in each of these four clusters, most significantly in the Government cluster (unsurprising given the location of Canada’s federal government). That Québec-based social media users under-index in each of these areas in entirely expected given that these conversations largely happen in the English language.
4.7 Suspected automation

Overlaying metadata on the network map, particularly when done in a series of graphics, helps us to visually understand areas of potential anomalies. Whilst strange patterns in the network can be in the form of clustering or ‘eccentricity’ of nodes or groups of nodes, it might also be found by looking at language or location, for example. The network map of Canadian COVID-19 conversation does not display many, if any obvious network anomalies, largely due to the ‘suspicious’ areas of the network forming genuine clusters due to their size. This is also the case when we consider the likelihood of automation in the network (figure 29).

Figure 29. Suspected automation per network entity

The visualisation above has been recoloured to show entities that are suspected to be automated. It is important to mention two points at this stage. Firstly, detection of automation online is far from a perfect science. Humans can act like bots in terms of their post frequency or sharing behaviours; whilst bots might very faithfully present human qualities of consideration and nuance. Therefore, identifying whether a Twitter account is automated is difficult at an individual level. However, given the number of automation accounts that do display traits associated with automation, such estimations are useful when made in the aggregate. Secondly, automation on social media is not necessarily a negative. Many media or political accounts rely on bots, as do weather, emergency service alerts or celebrity accounts. Automation is necessary on Twitter for a range of reasons, with accounts vying for space on users’ timelines. However, when analysed alongside network anomalies and what we already know...
about the ‘political’ areas of the network, it provides a useful filter through which we might find evidence of
disinformation. This is particularly relevant when we consider that automation to falsely inflate social media metrics
is one string to the bow of influence operations, gaining the trust of human Twitter users.

Nodes are classified as automated if they have posted more than 50 times per day since the account’s creation,
and are not Verified by Twitter. The latter step excludes the vast majority of automated media accounts from
mainstream outlets, organisational accounts and other trustworthy sources. Nodes suspected to be automated
have been recoloured black on the visualisation figure 29. It is clear that the political clusters in the network are
home to more prominent automated accounts (larger nodes).

Figure 30 below shows the proportion of automated accounts broken down by cluster. Firstly, the level of
suspected automation across the network is very low, particularly when compared to political debates in other
countries. For example, analysis of political and conflict-related conversation in Ukraine in 2019 and 2020 routinely
revealed more than 30% of the network to be automated. Just 5.8% of the Canadian COVID-19 network in the
reporting period was automated. This is possibly for two reasons. Firstly, the prominence of COVID-19 as a
significant issue across all of society means that a large volume of humans were drawn to the debate organically.
Secondly, the volume of content posted by ‘official’ accounts, particularly in the government and media, was also
high. Both of these factors meant that heavy bot activity may have been largely ‘drowned out’ from the network,
in favour of more reputable sources. The Anti-Liberal (11.37%), Progressive (13.36%) and Right-Wing (8.68%)
clusters were more likely to be automated, as a proportion of the neighbourhood.

Figure 30. Distribution of suspected automation per network cluster

Proportion of suspected automation
Segmented by network community
4.8 Active accounts

In a similar way, we can also overlay an entity’s status to better understand potentially suspicious areas of the network. Three account statuses indicate areas for further analysis when clustered or found in significant parts of the network. Firstly, an account could be “inactive”. This is where it has been cancelled by the user herself. It is a common tactic by influence operations to share large volumes of content on a given subject and then remove the account from public social media. Secondly, an account could have been “Suspended” by Twitter for breaking the platform’s terms and conditions, spreading hate, inciting violence or a raft of other reasons. Here, we are using Twitter’s own policing of the site to spot patterns. Lastly, an entity could be what we might call a “reset” account. This is where a handle is reused after it has been cancelled, most likely by a new user, as the account has a different Twitter ID.

Of course, given what was outlined in the methodology chapter of this report, in relation to President Trump, the network only displays inactive, suspended or reset accounts in two circumstances: either when it has been deleted or suspended since the data was originally captured in early 2021 (potentially months after posting about COVID-19) or because we have captured content that engaged these accounts, but doesn’t share them. We do not have access to the original tweet, not retweets of that content, if Twitter has removed that account from its database. Figure 31 below shows these account statuses across the network.

*Figure 31. Account status per network entity*
Figure 32 shows how these break down across the different clusters of the network. The Right-Wing cluster contained by far the highest proportion of inactive and suspended accounts. More than 5% of accounts in this cluster were manually removed, and more than 7% were suspended by the Twitter platform. Numbers were also high in the Anti-Liberal cluster, with 5.01% of accounts inactive here also. More than 5% of accounts in the Rebel News cluster were also suspended.

Figure 32. Distribution of account statuses per network cluster

Proportion of active accounts
Segmented by network community

4.9 Post volume

The visualisation below (figure 33) has reverted back to the original cluster colour-coding, but entities have been resized according to the volume of posts about COVID-19 in Canada in the reporting period: the larger nodes posted more frequently. Again, the data is visualised in this way to more easily identify network anomalies, but higher volume accounts are more likely to be found at a cluster-by-cluster level, than in micro-neighbourhoods in the network.

Rebel News cluster entities were the heaviest posters in 2020, contributing more than twice per person, per day about COVID-19 throughout the reporting period. The chart below (figure 33) shows COVID-19 volume (green dots) compared to all volume posted by these accounts (blue bars). Progressive cluster entities posted more than any other when we expand to all topics, with these accounts posting on average more than 31 times per day in 2020.
Rebel News cluster entities were the heaviest posters in 2020, contributing more than twice per person, per day about COVID-19 throughout the reporting period. The chart below (figure 34) shows COVID-19 volume (green dots) compared to all volume posted by these accounts (blue bars). Progressive cluster entities posted more than any other when we expand to all topics, with these accounts posting on average more than 31 times per day in 2020.
4.10 Daily mentions

More than 53 million individual mentions were captured for this report on the subject of COVID-19 in Canada, from March 1 to December 31, 2020. Nearly 41 million of these were tweets. The chart below (figure 35) shows the daily volume of content on all platforms, and on Twitter, across the 10 months. As is clearly shown, discussion peaked significantly at the beginning of March 2020, as the virus first hit headlines around the world, then arrived in Canada. Volumes dipped dramatically, to between 20% and 30% of its peak, before rising again briefly as a third wave of the pandemic hit the country in October 2020. A distinct weekly rise and fall is also visible, with media headlines and case statistics, both numbers that slow at the weekend, dominated coverage of COVID-19. Twitter stayed consistently between 70% and 80% of total volume throughout the period after March, where it rose to more than 88%.

Figure 35. Daily mentions of COVID-19 in Canada

Figure 36 (below) segmented this daily volume according to network cluster, and normalises the volume of each cluster, according to the number of members, to allow comparison more accurately across all clusters. The ‘political’ clusters again stand out on the chart as more active, and have thus been segmented further on figure 37.
The chart above (figure 36) shows two main features. Firstly, that both **Progressive** and **Rebel News** clusters were very active at the beginning of the pandemic. Both political poles reacted to the onset of COVID-19 in different ways, of course, but were brought to Twitter in equal measure to discuss and debate. Later in 2020, the **Right-Wing** cluster became more prominent, rivalling the **Progressive** cluster for daily volume across the second half of the year, and being the most active cluster in the network for much of this period, proportionally.

When we look at absolute volumes, we see that the **Progressive** and **Ontario** clusters dominated across the course of the reporting period. However, in November and December 2020, the Alberta network was much more vocal than previously, due to a significant rise in cases and criticism of Premier Jason Kenney. Provincial NDP leader Rachel Notley was particularly prominent in the discussion (figure 38).
4.11 Gender

Public social media conversation in the political world is a male-heavy issue almost globally. For a variety of reasons, social media users that identify as male generate around 60% of content in most online discussions on
public issues. This is further exaggerated as we move further to the right of the political spectrum, correlating with voter patterns in many parts of the world. Therefore, we might understand a 60:40 male-female split as the equilibrium. Gender is classified by an automated process that looks at names and online identities, not categorising social media users that cannot be confidently classified. Similarly, if a social media user identifies as one gender, then the automated process will classify the user as that gender: the analysis only uses information given by users themselves. This binary analysis is of course far from perfect. It does not recognise social media users that might identify as gender neutral or transgender, and contains a margin of error for the male and female genders that it does recognise. However, for the purposes of a snapshot, we can use the chart above (figure 39) to acknowledge the surface-level divide in Canadian COVID-19 conversation.

Across the network as a whole, more than 62% of all entities were classified as male, with this rising to 76% in the Rebel News cluster and 78% in the Québécois right-wing fringe (outlined on page 80).
5.0 The geographic and government clusters

5.1 British Columbia

In the British Columbia cluster, online impressions of COVID-19 can be broken down into three distinct sections: early-COVID-19 concerns, persistent COVID-19 frustrations, and post-COVID-19 progress. When the virus first made its way into Canadian borders, British Columbian concern was focused on risk of transmission. Before there were wide-spread restrictions, and acceptance of those restrictions, coverage of what was safe to do or not do, how the virus spreads, and the risk-level based on continuing different everyday activities dominated headlines.

As COVID-19’s stay in BC persisted and restrictions shifted based on changing case trajectory, concerns turned into confusion and frustration. Government and Public Health officials made use of social media platforms and traditional media to inform the public on case numbers, vaccine rollout, and restrictions. However, Premier John Horgan frequently came under scrutiny for the delivery of his restriction updates. A lack of clarity and short-notice were often pointed to by business owners and the general public when circuit-breakers, gathering limits, and other enforcement measures were introduced. It should be noted that this did not indicate reluctance to follow the restrictions, simply that the public felt under-informed.

Finally, as optimism toward a return to normal spreads through the province, many are commenting on the lessons learned through the pandemic and long-term policy changes that should be adopted. These include CERB popularity pointing to the need for a UBI, stronger investment in LTC homes, food insecurity, supports for women facing domestic violence, and the benefits of outdoor learning.

5.2 Alberta

In the Alberta cluster, online impressions of COVID-19 indicate two strongly opposed groups. On one side, many are quick to criticize Jason Kenney and the Albertan government for a failed response to COVID-19. Information mainly found on Twitter highlights several points of disapproval towards Premier Kenney’s actions. These include a lack of common-sense on restriction enforcement and using his position to overpower health officials and push his own political agenda. There is a specific focus among many Twitter users on failure in the area of jobs and economic recovery.

In contrast, an opposing side can be found highly active on Facebook. These individuals criticize public health officials and the restrictions being put in place, frequently speaking out against the rules and denying the severity
of COVID-19. There is an element of conspiracy theory included in this group, going as far as to claim the pandemic is nothing more than a fear tactic to control the public, and that the virus was deliberately released.

Though traditional media stayed relatively neutral, opinion-based articles on Premier Kenney’s COVID-19-response highlight a polarized public. While some point to a lack of leadership, others feel increased support is not the answer, as it creates a dependence on government aid.

### 5.3 Government

Government officials have made a concerted effort to share important information with the public throughout the pandemic. Government websites, press briefings, traditional media and personal social media use are geared toward easily accessible and straightforward information on matters most important to their communities. The broad messaging is stay safe, follow the guidelines, and get vaccinated. More specifically, this includes daily case numbers and deaths, changes in restrictions, promoting wearing a mask, relief and assistance programs available, and general information on vaccines. When promoting safe practices and vaccination, government sources frequently target those who may be skeptical of the severity of the pandemic or the safety of vaccines by highlighting the impacts of the virus and building confidence in vaccine science.

Non-government officials who interact with government content fall into two groups. A large portion acts as agents of the government, echoing their messaging by sharing information and encouraging their audience to follow the same protocols and advice. These individuals cite government sources to dispel misinformation. The second group acts in response to government information, at times criticizing government officials, questioning restrictions, and acknowledging vaccine hesitancy.

The main point of contention revolves around relief and benefit services provided throughout the pandemic. Small business relief, wage subsidy, and rental control are high areas of concern for online users, and commonly addressed by government officials.

### 5.4 Ontario

Similar to other provinces, Ontario has a high volume of individuals and outlets using their platforms to promote safety guidelines and encourage vaccination. There is a tendency to look forward to a reopening of the province, how and when it might happen, and what the province will be able to enjoy in a COVID-19-protected world. There is respect for post-secondary institutions and scientific communities, who frequently see their research shared online or covered in the media.

Ontarians are highly critical of how the provincial government has handled the pandemic. Consensus is that the government has failed in protecting the province. Many online users are advocating for common-sense restrictions
and better relief packages. Frequent topics include paid sick days, investment in LTC homes, pandemic pay to health care workers, protection from eviction, and increased aid to the homeless community.

Compared to other clusters where blame is more often spread to a few groups, Premier Ford is seen as a singular figure to blame for Ontario difficult struggle against COVID-19. He is accused of going against the advice of the public health agency. Though, he is often in the media deflecting blame and calling for unity in fighting the virus together.
6.0 The political clusters

6.1 Progressive

The *Progressive* cluster has a clearly defined line between individuals and COVID-19 efforts that require admiration and applause, and those that require shaming and criticism. Across all platforms, there is a strong sense of support for measures taken to prevent spread. Information shared frequently includes encouraging vaccination, continuous use of masks, and strict adherence to all public health safety protocols. Similarly, admiration is shown to healthcare workers and leaders in regions where the impact of COVID-19 has been limited (i.e.: Dr. Robert Strang of Nova Scotia and New Zealand Prime Minister Jacinda Ardern).

On the other hand, criticism and shame is quickly shown to regions where the spread of COVID-19 has not been controlled. There is fear that restrictions are being lifted too quickly, particularly with the CDC’s recent announcement lifting the mask mandate in the U.S. Criticism is often directed to the lack of leadership from various political leaders (i.e., Premier Jason Kenney, President Donald Trump and Ontario Premier Doug Ford)\(^9\).

---

\(^9\) [https://twitter.com/26aball/status/1295031709356957696](https://twitter.com/26aball/status/1295031709356957696)
Though, shame is also directed at the general public in these regions for not taking the pandemic seriously. Furthermore, large-businesses who have experienced significant COVID-19 outbreaks are attacked for their poor and inhumane working conditions. A highlighted example of this is the Tyson Foods Plant in Waterloo, Iowa10.

A common term among social media users on the left is “long COVID-19”. Long COVID-19 refers to the long-term symptoms and impacts of COVID-19 after initial infection. There is concern around the lack of information on the continuous effects of COVID-19. In a few instances, long COVID-19 is also used as a tool for encouraging individuals who don’t see the virus as a threat to get vaccinated.

The *Progressive* cluster has a clearly global outlook, in addition to domestic pandemic concerns. Publications such as *The Atlantic*, *The New York Times*, *CNN*, *The Guardian* and *Politico* provided a large number of the most influential media in the *Progressive* cluster, whilst discussions regularly discussed politics in the US and criticized the country’s pandemic response. The *Progressive* cluster also often linked COVID-19 to other civil liberties and equality-related social issues11.

---

10 https://twitter.com/MichaelGrabell/status/1341059824474329090
11 https://twitter.com/kid_prairie/status/1290137730777640962
6.2 Right-Wing

The Right-Wing cluster contributed many of the most extreme examples of COVID-19 measure resistance in the network. From an obsession with China as the origin of the virus\(^{12}\) to defending the response of the President of the United States Donald Trump, members of this neighbourhood of the network showed little contradiction to what we might consider to be typical right wing online conspiracy and ‘identity’ traits.

Common themes in the cluster included linking COVID-19 restrictions to totalitarianism, amid a wider concern for personal liberties\(^{13}\).

Sweden was often held up as the ‘poster boy’ of countries, early in the pandemic at least, in terms of how Canada might wish to relax restrictions. The general tone was, as perhaps expected, deeply in opposition to the current federal government and Prime Minister Justin Trudeau, lining the PM to other, ‘official’ institutions such as CBC and the World Health Organization (WHO). Themes of ‘liberty’ and ‘choice’ were linked to “patriotism” and a “fight for Canada’s future”, as members of the Right-Wing cluster railed against masks (seen as a particular evil) and other associated factors of COVID-19 response, such as lockdowns (and the effect of lockdowns), general public despondency and “fear” over the virus, and early signs of vaccine “choice”.

\(^{12}\) https://twitter.com/PaulMitchell_AB/status/1261610551555223552
\(^{13}\) https://twitter.com/SarahFischer__/status/1254442571679641600
A number of disinformation themes were present. The Right-Wing cluster was certainly home to the largest proportion of disinformation in the network, and the themes were multifarious. Early in the reporting period, COVID-19 was labelled a “bioweapon” by many in the cluster, originating in China and brought to Canada on a wave of federal corruption and “Globalisation”.

This narrative evolved towards the end of 2020, with vaccines seemingly taking over as the tool of manipulation, rather than the virus itself. It was somewhat widely believed that the virus was used to “subvert” the Canadian population and to control its people, and even the quantities of people. To this end, PM Trudeau was believed to be in league with Chief Public Health Officer Theresa Tam, and Director of the U.S. National Institute of Allergy and Infectious Diseases, Anthony Fauci, as well as philanthropist Bill Gates. An extension of this disinformation narrative claimed that COVID-19 existed prior to 2019, with highly spurious studies providing ‘evidence’ of this, shared online14.

Tools for spreading these master narratives included many seemingly wilful misinterpretations of official, and fabricated, data, both about the dangers posed by the virus and the efficacy of supposed cures. On the former, common themes of the virus being “no worse than the flu” were often posited, alongside claims that no Canadian has died of COVID-19 that did not have an underlying health condition. On the latter, hydroxychloroquine was widely seen as an answer to the pandemic in this network cluster in the middle of 2020. Entire websites were created and shared, spreading either entirely false, or simply exaggerated, statistics on the drug’s effectiveness15.

---

14 https://twitter.com/MoneCharl/status/1304028610211307523
15 https://c19hcq.com/
The nature of this cluster takes an even more rounded shape when we look at its affinities: accounts that over index in terms of followers from this cluster (Table 1).

More than half (54.37%) of all members of the Right-Wing cluster followed President Donald Trump (@realDonaldTrump), whilst other controversial right-wing figures in US politics covered the rest of the top spots: actor James Woods (@RealJamesWoods), Fox News anchor Tucker Carlson (@TuckerCarlson) and author and polemicist Candace Owens (@RealCandaceO). Analysis of these affinities can be used to both define and analyse centres of influence attached to a network community outside of content posted. Even if these influential social media users never posted in relation to Canada, they are influencing huge numbers of Canadians in this cluster with more general discussion. Likewise, table 2 below shows the most shared news domains in the Right-Wing cluster.

### Table 1. Leading affinities of the Right-Wing cluster

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Percentage of users</th>
</tr>
</thead>
<tbody>
<tr>
<td>Donald J. Trump</td>
<td>48th President of the United States of America</td>
<td>54.37</td>
</tr>
<tr>
<td>James Woods</td>
<td>This is the ONLY verified Twitter account for James Woods. I am also @RealJamesWoods on Instagram. Any other social media account using my name is a fake.</td>
<td>39.42</td>
</tr>
<tr>
<td>Tucker Carlson</td>
<td>Host of “Tucker Carlson Tonight,” weekly guest is @realDonaldTrump, my #1 NFT sellingboost #StopRacism. If you see him in a crowd, be prepared to beodonated — 0%</td>
<td>38.76</td>
</tr>
<tr>
<td>Candace Owens</td>
<td>New York Times bestselling author; Founder of BLM organization. Black people don’t have to be Democrats — 0%</td>
<td>35.14</td>
</tr>
<tr>
<td>Donald Trump Jr.</td>
<td>President Trump Jr.</td>
<td>34.70</td>
</tr>
<tr>
<td>James Otis</td>
<td>Guest judge, Project Veritas &amp; Project Veritas Action. I’m a fox/realfox @realDonaldTrump or we can use an encrypted Signal message at 814-690-3113</td>
<td>33.70</td>
</tr>
<tr>
<td>Jovenit</td>
<td>Paul Joseph Walker</td>
<td>32.90</td>
</tr>
<tr>
<td>Epis David</td>
<td>Relaxed commander of the story</td>
<td>32.87</td>
</tr>
<tr>
<td>Donald Trump Jr.</td>
<td>Donald Trump Jr.</td>
<td>32.87</td>
</tr>
<tr>
<td>Brockington</td>
<td>Brockton News</td>
<td>30.77</td>
</tr>
<tr>
<td>Ben Shapiro</td>
<td>Wshh’s “The Right Side of History” and How To Destroy America In Three Easy Steps</td>
<td>29.73</td>
</tr>
<tr>
<td>Sean Hannity</td>
<td>CNN’s “The New York Times Channel PM EST. On Twitter @seanhannity. Repeaters. Follow for endorsement due to backlinks, #CMXit</td>
<td>29.41</td>
</tr>
<tr>
<td>BobBeattyWright</td>
<td>Robert News</td>
<td>28.40</td>
</tr>
<tr>
<td>Charlie Kim</td>
<td>Founder &amp; CEO of The Daily Wire - The Daily Wire. Author - The MAGA Coalition We are all still here.</td>
<td>28.30</td>
</tr>
<tr>
<td>Louis Theroux</td>
<td>Author, Host, The Nancy Grace Show, Brett_M GRT, Host of The Ben Shapiro Show, The Right Side of History and How to Destroy America in Three Easy Steps</td>
<td>28.15</td>
</tr>
<tr>
<td>RebelNews</td>
<td>Rebel News</td>
<td>28.15</td>
</tr>
<tr>
<td>Canada.ca</td>
<td>Talking the other side of the story.</td>
<td>28.15</td>
</tr>
<tr>
<td>Charliitted</td>
<td>Charlie Kim</td>
<td>28.15</td>
</tr>
<tr>
<td>Linda McCall</td>
<td>Founder &amp; CEO of The Daily Wire - The Daily Wire. Author - The MAGA Coalition We are all still here.</td>
<td>28.15</td>
</tr>
<tr>
<td>Michelle Erdoğan</td>
<td>Author, Host, The Nancy Grace Show, Brett_M GRT, Host of The Ben Shapiro Show, The Right Side of History and How to Destroy America in Three Easy Steps</td>
<td>28.15</td>
</tr>
<tr>
<td>RebelNews</td>
<td>Rebel News</td>
<td>28.15</td>
</tr>
<tr>
<td>RebelNews</td>
<td>Rebel News</td>
<td>28.15</td>
</tr>
<tr>
<td>ThePostMillennial.com</td>
<td>Chief of Staff, Polite (Leader of the Nepotopop)</td>
<td>27.15</td>
</tr>
</tbody>
</table>

### Table 2. Most-posted domains of the Right-Wing cluster

<table>
<thead>
<tr>
<th>Domain</th>
<th>Volume of Shares</th>
</tr>
</thead>
<tbody>
<tr>
<td>youtube.com</td>
<td>58</td>
</tr>
<tr>
<td>torontosun.com</td>
<td>47</td>
</tr>
<tr>
<td>cbc.ca</td>
<td>40</td>
</tr>
<tr>
<td>globalnews.ca</td>
<td>30</td>
</tr>
<tr>
<td>ctvnews.ca</td>
<td>27</td>
</tr>
<tr>
<td>nationalpost.com</td>
<td>24</td>
</tr>
<tr>
<td>rebelnews.com</td>
<td>22</td>
</tr>
<tr>
<td>thepostmillennial.com</td>
<td>18</td>
</tr>
</tbody>
</table>
The concentration of disinformation narratives and more extreme thinking in this cluster makes it the place to start in future network mapping and analysis of the Canadian online space. Many of these actors continue to be heavily involved in COVID-19 disinformation spreading on Twitter, and can be monitored ongoing, alongside new accounts that may emerge in the neighbourhood.

With this insight to the Right-Wing cluster and its location of disproportionately high volumes of disinformation, it is crucial that we extrapolate this network. Figure 40 below shows this cluster’s expansion to a new network, outside of COVID-19, to give a better understanding of some of the techniques we might use in the future to better understand how COVID-19 narratives are related to different topics and online communities, and how information is spread between them. Figure 40 shows the accounts engaged by members of the Right-Wing cluster on all topics.

A split between US and Canadian issues is clearly evident, but within the same broad realm. The network shows the extent to which US figures influence the Canadian discussion on the right of online politics in a similar way to the affinities outlined on table 1, with the Canadian cluster being dominated by the People’s Party of Canada and its key political figures. In order to understand disinformation narratives that impact the COVID-19 debate in Canada, we need to look to the US for its qualitative origins.
6.3 Rebel News

The Rebel News cluster represents a small part of the network (just 1.75% of all entities) but its location and influence outside of its cluster is significant. Aside from mainstream networks CBC, CTV and Global, Rebel News was the most prominent media organisation in the entire COVID-19 network in Canada, with the fact that it represents a discreet segment of the map showing its significance on the right of Canadian online politics. Founder Ezra Levant (@ezralevant) and other Rebel News journalists form prominent centres of influence in this section of the Twitter network, between the Right-Wing cluster inhabited by the People’s Party of Canada (PPC) and the Anti-Liberal cluster, the home of the Conservative Party of Canada and shadow ministers.

Thematically, it’s perhaps driven by supply more than demand, given that Ezra Levant has a book to sell on the issue, the Rebel News cluster is chiefly focused on labelling China as the centre of virus blame, dubbing not simply COVID-19 but subsequent restrictions and measures as part of a “Chinese Communist Party” conspiracy, supported by “CCP propaganda”.

16 https://www.amazon.ca/China-Virus-Trudeaus-Pro-Communist-Canadians/dp/1777198615
Many of the semantic vehicles employed by members of this cluster to spread disinformation narratives are similar to that of the Right-Wing cluster in terms of deliberate misinterpretations of data and claims of ‘subversion’ by government actors. A particularly prominent disinformation narrative was posted in this cluster in the form of a supposed ‘leaked memo’ from “committee member within the Liberal Party of Canada”, published on thecanadianreport.ca. The blog made a range of fairly wild claims about Ottawa’s plans for the subsequent phases of the pandemic, all the way to “Deployment of military personnel into major metropolitan areas as well as all major roadways to establish travel checkpoints. Restrict travel and movement. Provide logistical support to the area. Expected by Q3 2021.”

As with the Right-Wing cluster, links to the US were very strong, especially on a tonal level: many of the media tactics seemingly originated in the US conservative cable news playbook. This is further emphasised by the table of affinities below (table 3).

17 https://thecanadianreport.ca/is-this-leaked-memo-really-trudeaus-covid-plan-for-2021-you-decide/
Table 3. Leading affinities of the Rebel News cluster

<table>
<thead>
<tr>
<th>Handle</th>
<th>Name</th>
<th>Description</th>
<th>Percentage of users</th>
</tr>
</thead>
<tbody>
<tr>
<td>Donald/Trump</td>
<td>Donald Trump (Trump-related)</td>
<td>EXP of Development &amp; Acquisitions, The @Trump Organization, Father, Outspoken in a past life Boardroom Advisor, On The Apprentice, Precious: Your Love</td>
<td>40.86</td>
</tr>
<tr>
<td>FlexAlmeroWoods</td>
<td>James Woods (Woods-related)</td>
<td>This is the ONLY verified Twitter account for James Woods. I am also @flexalmerowoods on Instagram. Any other social media accounts using my name is a fake.</td>
<td>44.44</td>
</tr>
<tr>
<td>TuckerCarlson</td>
<td>Tucker Carlson (Tucker-related)</td>
<td>Host of “Tucker Carlson Tonight”, who appears at 6 PM ET @FoxNews. My #1 NY Times bestselling book “The Lost Art of Winning” is out now.</td>
<td>44.18</td>
</tr>
<tr>
<td>charliek</td>
<td>Charlie Kirk (Kirk-related)</td>
<td>Founder &amp; President - @TheDailyShow. The Charlie Kirk Show - The MSGA Doctrine! We are all Chinese! China is our own!</td>
<td>42.07</td>
</tr>
<tr>
<td>AndyNig</td>
<td>Andy Nig (Nig-related)</td>
<td>Author of NYT Bestseller “Unburned” <a href="https://www.amazon.com/book/thegreatrace/dp/0385500521">https://www.amazon.com/book/thegreatrace/dp/0385500521</a> Editor-at-large @ TheRightRevolution</td>
<td>35.32</td>
</tr>
<tr>
<td>beranzapio</td>
<td>Ben Shapiro (Shapiro-related)</td>
<td>Editor, The Daily Beast. Host of The Ben Shapiro Show. He’s Right, He’s Side of History and “How To Destroy America In Three Easy Steps”.</td>
<td>41.08</td>
</tr>
<tr>
<td>JamesOkwari</td>
<td>James Okwari (Okwari-related)</td>
<td>Quartzia Journals, Project Veritas, &amp; Project Veritas Action. On the internet? <a href="mailto:ventriloquists@projectveritas.com">ventriloquists@projectveritas.com</a> or send us an encrypted Signal message at 614-653-3110</td>
<td>38.60</td>
</tr>
<tr>
<td>PolitiFact</td>
<td>Dave Rublin (Rublin-related)</td>
<td>Retired RIAF Superpower.</td>
<td>39.48</td>
</tr>
<tr>
<td>DrJordanBPeterson</td>
<td>Dr Jordan B Peterson</td>
<td>Toronto Psychology Professor. NOTE: RT follows are not to be read as endorsements. I sometimes post material with which I do not agree.</td>
<td>39.46</td>
</tr>
<tr>
<td>DailyCaller</td>
<td>Daily Caller (Caller-related)</td>
<td>The journalistic or news media.</td>
<td>37.61</td>
</tr>
<tr>
<td>TomFilson</td>
<td>Tom Filson (Filson-related)</td>
<td>President, Judicial Watch. These are my personal views only. NEW BOOK: A Republic Under Assault. <a href="http://judicialwatchbook.com/https://instagram.com/tomfilson">http://judicialwatchbook.com/https://instagram.com/tomfilson</a></td>
<td>36.76</td>
</tr>
<tr>
<td>ErikaLeaver</td>
<td>Erika Leaver (Leaver-related)</td>
<td>Former campaign manager of President Donald Trump. Former campaign manager of President Joe Biden.</td>
<td>41.03</td>
</tr>
<tr>
<td>SeanDoran</td>
<td>Sean Doran (Doran-related)</td>
<td>Co-founder of FREE SPEE, writer, that has worked with the National Rifle Association, climate change is a hoax, former chief of staff for Sen. Tom Coburn, Wharton grad.</td>
<td>35.90</td>
</tr>
<tr>
<td>PragerU</td>
<td>Paul Joseph Watson (Watson-related)</td>
<td>“Watson-ism” is a brilliant political commentator!” The Spectator, “Popular cutting-edge political commentator!” The Jewish Voice - Telogis: <a href="https://twitter.com/prageru">https://twitter.com/prageru</a></td>
<td>35.60</td>
</tr>
<tr>
<td>NavyOsborne</td>
<td>Jack Osbome (Osbome-related)</td>
<td>Veteran Navy Intelligence officer.</td>
<td>35.47</td>
</tr>
<tr>
<td>realDonaldTrump</td>
<td>Donald J. Trump (Trump-related)</td>
<td>45th President of the United States of America?</td>
<td>38.84</td>
</tr>
<tr>
<td>Dr.couch</td>
<td>Dana J. couch (Couch-related)</td>
<td>Nominated senatorial talk radio host 12-2am ET. author, #4A advocate, dog lover, former goth kid, often immersed. Thrilled by Twitter.</td>
<td>38.35</td>
</tr>
</tbody>
</table>

To further emphasise these relationships with the right of US politics, we again extrapolated the network from its COVID-19 origins, mapping users across all topics. As with the Right-Wing cluster (shown on figure 41) the network shows a near 50:50 split, Canada-US entities. In fact, we might even understand Rebel News as either a bridge between Conservative media in the United States and right wingers in Canada, or even as a very influential vehicle that carries extreme narratives and sentiment to a Canadian audience, via its Canadian founder. We would need further investigation, as mentioned previously, to better attribute sentiment and intension, but there is no doubt that, as an organisation, Rebel News is one of the most significant centres of influence the Canadian COVID-19 discussion.

Figure 41. Expansion of the Rebel News cluster
### Table 4. Most-posted domains of the Rebel News cluster

<table>
<thead>
<tr>
<th>DOMAIN</th>
<th>VOLUME OF SHARES</th>
</tr>
</thead>
<tbody>
<tr>
<td>rebelnews.com</td>
<td>40</td>
</tr>
<tr>
<td>torontosun.com</td>
<td>16</td>
</tr>
<tr>
<td>nationalpost.com</td>
<td>13</td>
</tr>
<tr>
<td>ctvnews.ca</td>
<td>12</td>
</tr>
<tr>
<td>nypost.com</td>
<td>9</td>
</tr>
<tr>
<td>youtube.com</td>
<td>9</td>
</tr>
<tr>
<td>tnc.news</td>
<td>8</td>
</tr>
<tr>
<td>globalnews.ca</td>
<td>8</td>
</tr>
<tr>
<td>cbc.ca</td>
<td>8</td>
</tr>
<tr>
<td>thepostmillennial.com</td>
<td>7</td>
</tr>
<tr>
<td>theglobeandmail.com</td>
<td>5</td>
</tr>
<tr>
<td>foxnews.com</td>
<td>5</td>
</tr>
<tr>
<td>thestar.com</td>
<td>3</td>
</tr>
<tr>
<td>nytimes.com</td>
<td>3</td>
</tr>
<tr>
<td>dailywire.com</td>
<td>3</td>
</tr>
<tr>
<td>justthenews.com</td>
<td>3</td>
</tr>
<tr>
<td>msn.com</td>
<td>3</td>
</tr>
<tr>
<td>truepundit.com</td>
<td>3</td>
</tr>
<tr>
<td>thehill.com</td>
<td>2</td>
</tr>
<tr>
<td>newsweek.com</td>
<td>2</td>
</tr>
</tbody>
</table>

#### 6.4 Anti-Liberal

Also, on the right of centre, the network segmented what might be called the *Anti-Liberal* cluster, whilst this community undoubtedly shares connections, both in terms of online engagement and narratives, with the more extreme elements of the political right in Canada and the US, the tone and membership of the *Anti-Liberal* is markedly more moderate in nature, defined as much by its political and ideological opposition to the Liberal Party government as anything else.\(^{18}\)

\(^{18}\) https://twitter.com/DanAlbas/status/1289188724476018689
The cluster contains a number of prominent CPC MPs and shadow ministers, and the party’s leader Erin O’Toole, and its members are much more likely to share ‘mainstream’ media sources, such as CBC, than publications towards the extremes of political discourse (shown on table 5 below).

Table 5. Most-posted domains of the Anti-Liberal cluster

<table>
<thead>
<tr>
<th>DOMAIN</th>
<th>VOLUME OF SHARES</th>
</tr>
</thead>
<tbody>
<tr>
<td>cbc.ca</td>
<td>106</td>
</tr>
<tr>
<td>torontosun.com</td>
<td>97</td>
</tr>
<tr>
<td>nationalpost.com</td>
<td>73</td>
</tr>
<tr>
<td>globalnews.ca</td>
<td>71</td>
</tr>
<tr>
<td>ctvnews.ca</td>
<td>53</td>
</tr>
<tr>
<td>thepostmillennial.com</td>
<td>44</td>
</tr>
<tr>
<td>tnc.news</td>
<td>43</td>
</tr>
<tr>
<td>blacklocks.ca</td>
<td>30</td>
</tr>
<tr>
<td>theglobeandmail.com</td>
<td>24</td>
</tr>
<tr>
<td>cp24.com</td>
<td>20</td>
</tr>
<tr>
<td>youtube.com</td>
<td>17</td>
</tr>
<tr>
<td>spencerfernando.com</td>
<td>14</td>
</tr>
<tr>
<td>nytimes.com</td>
<td>11</td>
</tr>
<tr>
<td>dailymail.co.uk</td>
<td>10</td>
</tr>
<tr>
<td>financialpost.com</td>
<td>10</td>
</tr>
<tr>
<td>bloomberg.com</td>
<td>10</td>
</tr>
<tr>
<td>toronto.ctvnews.ca</td>
<td>9</td>
</tr>
<tr>
<td>edition.cnn.com</td>
<td>9</td>
</tr>
<tr>
<td>rebelnews.com</td>
<td>8</td>
</tr>
<tr>
<td>edmontonjournal.com</td>
<td>7</td>
</tr>
</tbody>
</table>
Tonally, discussion contained few outright narratives of disinformation, but no less criticism of the Canadian government’s COVID-19 response, the WHO and other ‘globalist’ actors. It is important to note at this stage the significance of association and network location of specific actors. One’s location in the network is no accident. It is an objective assessment based on patterns of online connections. Therefore, whilst prominent CPC politicians might not be openly engaging in criticism of Sophie Trudeau’s COVID-19 diagnosis, for example, their content is consumed and shared and engaged by social media users that do involve themselves in such narratives. Or even connections-of-connections, defining a social media user on who their friends are.

Whilst actors in this cluster were critical of mask mandates, border closures (or delays to border closures) and accusations of a lack of “parliamentary process” in Ottawa, due to pandemic restrictions, there was a broad level of recognition of the seriousness of COVID-19.

This is arguably the most significant difference between the Right-Wing and Rebel News clusters and more moderate elements on the right, and why the Anti-Liberal cluster would not be at the beginning of the search for disinformation narratives in future Canadian networks.

Table 6. Leading affinities of the Anti-Liberal cluster

<table>
<thead>
<tr>
<th>Handle</th>
<th>Name</th>
<th>Description</th>
<th>Percentage of users</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brian_k</td>
<td>Brian Lilley</td>
<td>Political columnist for the Toronto Sun. I write about federal and Ontario politics. Sometimes other stuff. I tweet about @NOFootba...</td>
<td>58.85</td>
</tr>
<tr>
<td>Pierre_Pouliot</td>
<td>Pierre Pouliot</td>
<td>MP for Carleton</td>
<td>56.12</td>
</tr>
<tr>
<td>Andrew_Scheer</td>
<td>Andrew Scheer</td>
<td>Regina – Q’Appelle MP. 2nd Conservative Party Leader and 35th HOC Speaker. Principal Conservative. Defender of economic freedom and human rights.</td>
<td>56.27</td>
</tr>
<tr>
<td>Michal_Hempel</td>
<td>Michal Hempel</td>
<td>Fortis AI. Canadian Member of Parliament. Vice Chair of the Health Committee. Wife of a US Army combat veteran. Shadow Minister for Health. Shelfer.</td>
<td>55.10</td>
</tr>
<tr>
<td>Louise_Goldstein</td>
<td>Louise Goldstein</td>
<td>Editor Emeritus. Columnist. Toronto Sun/Sun Media; commentator. Arena Byron Show. Sirius XM Ch. 167. email: <a href="mailto:lgoldstein@postmedia.com">lgoldstein@postmedia.com</a></td>
<td>54.08</td>
</tr>
<tr>
<td>Candice_Malcolm</td>
<td>Candice Malcolm</td>
<td>Journalist, bestselling author, columnist for the Toronto Sun.</td>
<td>52.48</td>
</tr>
<tr>
<td>Jason_Kenney</td>
<td>Jason Kenney</td>
<td>Premier of Alberta. Focused on protecting lives and livelihoods. <a href="http://www.alberta.ca/stopthespikes">http://www.alberta.ca/stopthespikes</a></td>
<td>52.21</td>
</tr>
<tr>
<td>Erin_Otto</td>
<td>Erin Otto</td>
<td>Husband, father, Leader of the Official Opposition @CPC_HQ, MP for Durham /Mat, pier, chef de l'Opposition officielle @PCC_HQ, député de Durham</td>
<td>49.56</td>
</tr>
<tr>
<td>Anthony_Furey</td>
<td>Anthony Furey</td>
<td>Columnist/editor for Sun papers/Postmedia <a href="mailto:alrey@postmedia.com">alrey@postmedia.com</a></td>
<td>48.69</td>
</tr>
<tr>
<td>Lisa_Raft</td>
<td>Lisa Raft</td>
<td>Rude or offensive and you’ll be blocked.</td>
<td>49.13</td>
</tr>
<tr>
<td>Candace_SergentMP</td>
<td>Candace Bergen</td>
<td>Canadian Member of Parliament serving Portage-Lisgar since 2008 &amp; @CPC_HQ Deputy Leader. Keep up to date on Facebook &amp; Instagram @CandaceSergentmp</td>
<td>49.13</td>
</tr>
<tr>
<td>Doug_Ford</td>
<td>Doug Ford</td>
<td>Premier of Ontario &amp; Leader of the @OntarioPCParty • For The People</td>
<td>49.71</td>
</tr>
<tr>
<td>Alex_GerstonAMP</td>
<td>Alex Gerston</td>
<td>Award winning Journalist. TV/Radio. Host @ AM 640, 900 CHML, and AM 680 News. Opinions are my own.</td>
<td>47.08</td>
</tr>
<tr>
<td>SpencerFernando</td>
<td>Spencer Fernando</td>
<td>Canada's best &amp; most modest writer / Campaign Fellow @WhatCitizens</td>
<td>46.94</td>
</tr>
<tr>
<td>Rachel_Duran</td>
<td>Rachel Duran</td>
<td>Team Lawyer</td>
<td>British Columbia</td>
</tr>
<tr>
<td>CPC_HQ Conservative</td>
<td>CPC_HQ Conservative</td>
<td>Canada’s Official Opposition, led by @ercotech. Four ie français, suiver @PCC_HQ</td>
<td>41.28</td>
</tr>
<tr>
<td>Vital_Krause</td>
<td>Vital Krause</td>
<td>Following the money. Check out our first film, Over A Barrel: <a href="http://www/says35.com">http://www/says35.com</a></td>
<td>46.06</td>
</tr>
<tr>
<td>Joe_Warington</td>
<td>Joe Warington</td>
<td>Columnist. Toronto Sun. Regaining Reader’s Choice gold medalist. Retweets are informational. Not endorsements. I treat this as news, opinion and humour sharing.</td>
<td>45.19</td>
</tr>
</tbody>
</table>

19 https://twitter.com/ShabnamHamseda/status/1242414586483093504
6.5 The Québécois fringe

As discussed previously in this chapter, the Québécois cluster exists largely for reasons of language. Therefore, we need to investigate further to identify areas of potential disinformation and political ideology in the same way that we did with other areas of the English-speaking network. Visual analysis of this neighbourhood showed a division in the network, with one area of the cluster leaning more heavily to the political right in the English language. A further of the segmentation algorithm confirmed this (figure 42).

Figure 42. Segmentation of the Québécois cluster

For ease, these two areas of the cluster, sub-clusters if you will, have been labelled Dissent and Mainstream, due to their COVID-19 stance, rather than an overt political ideology. The Dissent subcluster was therefore segmented and analysed further.

Visible are narratives similar to that identified on the political right in the English language: doubting the validity of the pandemic, claims of a Chinese conspiracy to overtake the United States in the global economic race, and claims that the data has been exaggerated and that COVID-19 is no worse than the flu.20

20 https://twitter.com/RaymondHarvey/status/1313495051377561605
The similarity brings questions over the amount of overlap between actors in the English and French languages in terms of extreme views and disinformation. Given the simple observation that the majority of members of the English-language Canadian online right are unlikely to speak French, it might be assumed that social media users in Québec are engaging in the same conspiracies and narratives via the global English conversation, especially given the links in this area of the overall network (figure 43).

Figure 43. Links between English and French extremes

This is further exemplified by the table of affinities (Table 7). The number of English language accounts influencing the fringe of the French language cluster in Canada shows the narrative overlap.
Table 7. Leading affinities of the Québécois fringe

<table>
<thead>
<tr>
<th>Handle</th>
<th>Name/Description</th>
<th>Percentage of users</th>
</tr>
</thead>
<tbody>
<tr>
<td>@realDonaldTrump_33</td>
<td>Chez le Parlement des États-UnisPresident Donald Trump’s account, maintained by the National Archives and Records Administration</td>
<td>45.54</td>
</tr>
<tr>
<td>@reuters</td>
<td>Moniteur Reuters</td>
<td>30.75</td>
</tr>
<tr>
<td>@WSJ</td>
<td>Moniteur de l'Économie</td>
<td>16.24</td>
</tr>
<tr>
<td>@CNN</td>
<td>Moniteur d'ABC</td>
<td>15.67</td>
</tr>
<tr>
<td>@CNN</td>
<td>Moniteur de l'Économie</td>
<td>7.74</td>
</tr>
<tr>
<td>@FoxNews</td>
<td>Moniteur de Fox News</td>
<td>6.76</td>
</tr>
<tr>
<td>@Trump</td>
<td>Moniteur de Trump’s account, maintained by the National Archives and Records Administration</td>
<td>6.53</td>
</tr>
<tr>
<td>@WSJ</td>
<td>Moniteur de l'Économie</td>
<td>6.53</td>
</tr>
</tbody>
</table>

Similarly with the table of the most shared media domains below (table 8). The number of high-profile English-language sources is clear.

Table 8. Most-posted domains of the Québécois fringe

<table>
<thead>
<tr>
<th>DOMAIN</th>
<th>VOLUME OF SHARES</th>
</tr>
</thead>
<tbody>
<tr>
<td>ici.radio-canada.ca</td>
<td>16</td>
</tr>
<tr>
<td>lapresse.ca</td>
<td>12</td>
</tr>
<tr>
<td>youtube.com</td>
<td>4</td>
</tr>
<tr>
<td>forbes.com</td>
<td>3</td>
</tr>
<tr>
<td>cbc.ca</td>
<td>3</td>
</tr>
<tr>
<td>tvanouvelles.ca</td>
<td>2</td>
</tr>
<tr>
<td>montrealgazette.com</td>
<td>2</td>
</tr>
<tr>
<td>lesoleil.com</td>
<td>2</td>
</tr>
<tr>
<td>foxnews.com</td>
<td>2</td>
</tr>
<tr>
<td>tnc.news</td>
<td>2</td>
</tr>
<tr>
<td>globalnews.ca</td>
<td>2</td>
</tr>
<tr>
<td>ctvnews.ca</td>
<td>2</td>
</tr>
<tr>
<td>hannity.com</td>
<td>2</td>
</tr>
<tr>
<td>montreal.ctvnews.ca</td>
<td>2</td>
</tr>
<tr>
<td>bmj.com</td>
<td>2</td>
</tr>
<tr>
<td>technocracy.news</td>
<td>2</td>
</tr>
<tr>
<td>washingtonpost.com</td>
<td>2</td>
</tr>
<tr>
<td>torontosun.com</td>
<td>2</td>
</tr>
<tr>
<td>zero Hedge.com</td>
<td>2</td>
</tr>
<tr>
<td>change.org</td>
<td>2</td>
</tr>
</tbody>
</table>
7.0 Issues of race, sexuality and Indigenous Canadians

This report also looked at areas in the discussion that impact minority groups within Canada, for two primary reasons: these groups are arguably disproportionately impacted by the pandemic; and these groups are often disproportionately impacted by the impact of disinformation narratives online. Sub-searches were created within the main Boolean query to better understand conversations around these issues. Searches included regular and derogatory terms for people in this communities, including slang.

By far the most significant narrative linked to race in the Canadian COVID-19 discussion surrounded anti-Asian and anti-Chinese sentiment, based on the origin of the virus and escalation in violence towards members of the Chinese community globally in 202021.

Figure 4 shows the distribution of race-related conversations in the network (green nodes show an entity that discussed race in the reporting period – 79.29% - a huge number).

---

[21](https://twitter.com/rpoconnor/status/1240329238168961026)
The issue was prominent in all main clusters in the network: those on the Progressive side of the network were largely critical of supposed racist politics and actions in the media, in response to the pandemic, and largely supportive of minority communities. 

22 https://twitter.com/GadflyQuebec/status/1266167353546608640
On the political right, racism was expressed by using such terms mockingly\(^\text{23}\), and to show an apparent lack of government focus, and as an offensive diminutive.

*Black Lives Matter* were also used by the right as a proxy for inconsistent policies in the US and Canada. Members of the political right were largely keen to point out that they are “not racist”, merely stating facts, such as on the origin of the virus.

This was also the case with Indigenous and LGBT issues in the network. Figure 45 and figure 46 below show the distribution of these topics across clusters.

*Figure 45. Entities discussing issues of Indigenous Canadians within the COVID-19 debate*
Firstly, these issues were far less likely to be discussed than issue of race. Slightly more than a quarter of the entities in the network address issues related to Indigenous Canadians and COVID-19 in the reporting period (27.91%) whilst less than a third (30.21%) discussed topics related to sexuality. There could be a number of reasons for these discrepancies when compared to issues of race. Firstly, simply that Canadians that are active in the public online discussion around COVID-19 did not perceive these communities to be as worthy of discussion or strong opinion. Secondly, that the media was less likely to address issues of sexuality or Indigenous Canadians in relation to the pandemic, and that there was less online content to be shared. Or lastly, that those engaged in the online debate did not consider the pandemic to impact minority groups of sexuality or Indigenous identity in the same way that it impacted people of colour.

Another view is also possible. Analysis of the network visualisations above show that discussions of sexuality and Indigenous Canadians were far less likely in right wing clusters than issues of race. Canadians on the right were less likely to use homophobic or anti-indigenous slurs within conversation about the pandemic than terms related
to race. Anti-Indigenous language was almost invisible across the network, whilst homophobic content was largely posted to criticize the government’s perceived priorities\textsuperscript{24}.

Further study is necessary to understand the evolution of these topics, particularly given recent tragic discoveries at Residential Schools in British Columbia and Saskatchewan, and deeper detail on the impact of COVID-19 on minority groups in Canada.

\textsuperscript{24} https://tnc.news/2020/09/21/liberals-fund-studies-on-transgender-peruvians-how-blm-helps-with-pandemic-coping/v
8.0 A brief note on the web network

A discussed in the methodology chapter of this report, the same methodology can be applied to look beyond Twitter, linking websites by backlinks and other connectivity.

As an introductory step, this methodology was trialled within this project. Figure 47 below shows the resulting network segmentation.

*Figure 47. The web network*

In short, the network is messy and does not cluster in the same way as a social media network. This is largely due to the fact that websites are less likely to cluster ideologically, linking to a variety of different sites based on advertising links and other affiliations. However, with patience, the web network yields tightly clustered networks of disinformation using the same theory, such as with *Project Avalon (projectavalon.net)* to the right of the map.
This tight cluster of sites all link back to *Project Avalon* and its content, including links to UK conspiracy theorist David Icke, discussion of “The Global Takeover” and “Plandemic resistance”\(^{25}\).

This area of analysis needs to be explored much more thoroughly to yield its potential. It is a lot more manual than Twitter analysis, for example, but the methodological similarities can be used to uncover dangerous disinformation narratives away from public social media, in the darker areas of the web.

9.0 Beyond this project

The most important element of this report is the outline of possibilities for the future. Data used in this analysis, due to a range of methodological routes, project delays and internal processes, is at a minimum more than six months old at the time of publication, and at the most more than 18 months old. Even in a world where, as previously outlined, online ‘neighbourhoods’ remain reasonably stable, data captured at the beginning of 2020 should no longer be used to compile actionable responses. This has been exacerbated by the sheer pace at which the COVID-19 discussion evolves and new sub-topics ebb and flow. Discussions that dominate in the summer of 2021: around vaccines; third and fourth waves of the pandemic; new lockdowns and restrictions; new mask mandates and changes to the political environment in the United States, in particular, each have the power to ‘reshape the network’. The sheer volume and emotion around these issues will have undoubtedly changed the structure and segmentation of the Canadian online environment, forming new and different online communities, new affiliations and loyalties, new identities and new centres of influence.

Figure 48. COVID-19 discussion in Nova Scotia on Twitter, March 2020
Figure 48 shows discussion around the COVID-19 pandemic in Nova Scotia in the first three months of 2021, on Twitter. The visualisation format is the same as in each previously shown in this report: the most influential 36,697 entities in the network are connected by 76,021 edges. As is clear from the visualisation, some political allegiance is found in the network. This is perhaps to be expected, given the route towards a potential provincial election in the province before the year is out, not to mention federal events. However, what is more distinct is a consolidation into two factions: 'mainstream' sources, health authorities and government, and the majority of the media; and a smaller community actively campaigning against pandemic restrictions (nearly 10% of the network). This is somewhat consistent with what we saw at a national level in 2020, with the natural absence of province-linked clusters and a genuine far-right presence in Nova Scotia, but the polarisation of the debate, in support of preventative measures, and against, shows that the ‘structure’ of the conversation is changing, and perhaps becoming more simplistic. It also shows the importance of outlining iterative and new routes of analysis, within the same realm.

This further analysis takes a range of possibilities, that largely fall into three camps.

1. Using the findings of this, and future analysis, to define counter-disinformation strategies.

2. Using this analysis to better define routes of future analysis, introducing new datasets, methodologies and subject matters.

3. More ‘forensic’ investigation into these phenomena, as a means to better tackling disinformation at its source.

This report introduces these concepts and identifies natural next steps in the continuation of this analysis within the three areas identified. However, although some of these methodological concepts are closely related to work that has already been undertaken, many are new and involve brand new areas of expertise: social listening is very different to what is known as ‘true OSINT’, for example. At this stage, outside experts and organisations would need to be introduced to the process.

9.1 Response strategies

We should not fall into the common trap of envisioning that social media, let alone the public-facing portion of social media, is the ‘real world’: online conversations, especially on Twitter, are innately unrepresentative of real life, with a range of both push and pull factors determining why different demographic, economic, educational or behavioural cohorts of people would want, and not want, to publish their personal opinions. Then, of course, we have the unnatural biases of the platforms themselves; algorithmically, and opaquely, promoting certain content
to content groups of people for reasons of user experience and dollars. Inferences made beyond social media data from social media data should be treated with extreme caution.

However, open-source information captured by social listening methodologies is inherently unsolicited and without anonymity. Unlike traditional polling, for example, we receive verbatim content posted by real people in Canada on the issue of COVID-19. On the other hand, unlike focus groups for example, we can analyse data at significant scale to better understand its level of representation. Therefore, insight derived from online sources can very effectively be used to construct online strategies, both at micro and macro levels. This project provides both a top-level analysis of what is happening across the entire country over a period of 10 months of significant social upheaval, but it also provides the raw data (where ethical considerations permit) to connect with small groups of people or individuals. We have successfully segmented Canadian COVID-19 conversation into social factions and overlaid an understanding of media consumption, demographics and decision-making inferences. We have analysed exactly the areas of this national conversation for further focus. In short, this project analyses who the entities are, and how we might engage them.

At a micro level, we might simply target social media advertisements and awareness campaigns at groups of people. These might range from people resistant to vaccination, or those that are influenced by sources from outside of Canada, where the COVID-19 situation is very different. There is also an efficiency factor. There are online clusters that will never be receptive to government messaging on the pandemic, for example, for both qualitative and quantitative reasons: a mistrust of ‘official’ sources, for example, on one hand; on the other, a social media network that simply doesn’t easily ‘permit’ the movement of information to its fringes. In a battle over dollars, we might choose to avoid these areas of social media when targeting information campaigns.

Of course, the raw data gives the power to target specific people, rather than types of people on social media. Here is where we might consider the ethics of social media advertising more closely, especially around government departments and agencies holding information on individuals and using it engage them, without their direct consent. As previously discussed, the private sector has fewer worries. A company might argue that the idea of ‘legitimate interest’ infers that a social media user that publishes content that mentions their brand understands that that data might be captured for commercial reasons. In short, Government should not rely on such an inference in the same way, for reasons of public trust and, ultimately, more effective communications.

At a macro level, recipients of this analysis could use its information to build comprehensive communications campaigns aimed at changing the online, and possibly offline, behaviour of Canadians over years, on this issue and beyond.

Ambitious programs could aim to change the nature of the network itself, and close gaps between the network’s fringes and its mainstream. This, of course, incorporates a recognition that information doesn’t truly travel across the COVID-19 online network, but merely between entities in the same clusters, in the main. And, where
information does cross into different neighbourhoods, it does so via a relatively small number of social liaisons. Both of these factors mean that it is difficult, or even impossible, for ‘mainstream’ or ‘official’ sources of information to reach social media users in a number of areas of the network with meaningful, behaviour-changing information around COVID-19.

This is where our social liaisons should be involved, or ‘influencers’ as they are more often called in digital circles. Using these centres of influence is the simplest way to change the structure of the network and to close gaps between clusters. Of course, this process is infinite in possibilities, particularly when extrapolated into what we might call broader online and offline ‘society’. Can we use these tools to bring Canadians together more generally?

A similarly grand scheme would aim to change the structure of the network by virtue of ‘educating’ users in some of its darker corners. This is where media literacy programs could be introduced to inform the general public of the function of media more generally, the importance of checking and researching sources, and making transparent information around online gatekeepers to information. The latter covers human and automated social media accounts that have become gatekeepers to digital information in the same way that journalists and politicians were in the analogue world; and the social media algorithms that dictate exactly who sees what information, how and when. The availability of knowledge on how such centres of influence perform their role in an online network is paramount to being able to trust sources. Network analysis around COVID-19 in this report has very clearly shown the areas of the online world, and perhaps beyond, where such knowledge would have a greater benefit.

**Alerts and monitoring**

Possibly the simplest ‘next step’ to apply from this report is the implementation of online monitoring and alerts around the topic of COVID-19 in Canada.

Social listening alerts are applied in three main ways.

1. We can monitor the movements of an account or groups of accounts. Of course, as discussed previously in the context of personal data protection, monitoring would need to concentrate on nefarious activity, centres of influence (or accounts with ambitions of influence), ‘publishers’, aggregated or anonymized social media accounts. Monitoring would also need to track account IDs or other unique identifiers in addition to account handles, due to the speed at which bad actors change their online identities. More pertinent, this report has identified both the specific and the types of accounts that are significantly more likely to engage in spreading disinformation online, removing the need to ‘guess’ topics of disinformation or be completely blinded by sheer data volumes when monitoring.
2. Monitoring of keywords and phrases associated with disinformation narratives. As with the point above, semantic analysis of the conversations within each cluster can reveal areas for future monitoring. This can be dovetailed with accounts for more accurate application.

3. Monitoring of data volumes. If points 1. and 2. above cover the known unknowns, then by monitoring changes in volumes of data we might get some of the way to understanding the unknown unknowns. By monitoring surges in the usage of particular phrases, in particular network clusters, we can understand data volumes in the wider context of ‘normality’, and better attribute a reason why the online conversation has changed. For example, if mentions of “hydroxychloroquine” in the far-right map neighbourhood suddenly exploded by 300% compared to a normal day, should we attribute that to a news event, an online centre of influence, or bot activity?

Alerts in email form can be linked to each of these monitoring scenarios, to update important stakeholders as things happen. Alert taxonomy is also easily updatable with subsequent iterations of this research. In brief, by isolating the hotspots, the network has allowed us to train our monitoring and alerts, and our human eyes, on the most important areas of the discussion from a disinformation perspective, rather than trying to accurately understand tens of millions of online conversations.

9.2 Further analysis

Further analysis of the data in this report could take two routes.

1. Subjecting the same data to different analysis methodologies. This could be differentiated by the analysis itself or the tools and software used to analyse the data.

2. Exploring narratives and themes that are tangential to the topic of COVID-19 in Canada, those that were discovered during the first phase of analysis, or those that have naturally emerged as the subject has evolved.

Technology

When we look towards alternative analysis methodologies, we might consider a range of options.

Deeper semantic analysis using Natural Language Processing engines would better understand the patterns of words and phrases in the discussion, how they change over time and what events and stimuli initiate these changes. For example, analysis performed by this author of patterns of conversation around the Notre Dame cathedral fire in Paris in April 2019 showed that narratives created in far-right clusters of the network, around
fictional claims of Islamic arson at the cathedral, quickly spread to the core of the network in the subsequent 36 hours and became what was considered to be a mainstream rumour, and even one side of a ‘debate’. This analysis was achievable by combining network analysis and minute-by-minute keyword usage patterns.

Might we also cluster a network based on the language of a social media account user, rather than its connections? Would we see linguistic similarities across ostensibly disparate areas of the network? Is there a language of the extremes in the network that is different from the mainstream, in effect creating two poles in the ‘debate’ rather than multiple centres of influence? This analysis would require detailed taxonomies of keywords and phrases, drawing connections between tonal similarities, rather than simply usage of the same words. Of course, we would also need to perform this across multiple languages.

Another semantic analysis route might incorporate Named Entity Recognition (NER). Using an NER engine, we could extract proper nouns, dates and times, locations, publications and other keywords to better understand trends and centres of influence. Is there a date that known disinformation accounts continue to mention? Might they constantly refer to a specific person that isn’t on social media and therefore is not part of the online network in the usual way? This also moves us into areas of using network analysis to understand influence on non-social media platforms, where accounts cannot engage each other but readers are still drawn to specific centres of influence.

Lastly, we might explore further analysis of our data to better understand the profiles of each cluster by enriching the data with demographic and behavioural data, and extrapolating. The Audiense data in this report shows the value of inferring gender and age from aggregated social media data using dictionaries of names, but tools such as Demographics Pro would take this further by using a variety of manual and automated taxonomical approaches to demographic analysis – as many as 10,000 datapoints per social media user. This data would be crucial to better tailoring smaller elements of mass communications campaigns, for example. In a similar way, social media advertising ‘onboarding’ platforms also enrich audiences using cookie data to understand browsing habits. This is done in an anonymized and aggregated way, but again leads to a very detailed understanding of social groups uncovered in the network, that would make it easier to both profile them and to reach them.

The structure of the data in this project makes it straightforward to tackle further analysis, via export and import functionality.

It is also possible to explore different types of social media data away from semantic searching: namely, image and video. Millions of images and videos are posted discussing the pandemic every week, with a significant proportion of these likely to be disinformation. But they might not mention keywords associated with the virus, and therefore not be captured using the Boolean search undertaken in this research. Here, we have two options.
Image recognition software will identify logos, objects and even facial expressions with public social media posts. It will also dissect a video into frames and analyse in a similar way. Social media is increasingly becoming video-first, dominated by YouTube, TikTok, Instagram and Facebook. This content is also arguably more influential, specifically among younger generations. The special listening capturing techniques used in this research simply cannot scrape videos or images where keywords are not mentioned alongside in text form.

Of course, a crucial aspect of video and image analysis is the recognition of doctored content. The fast-growing field of ‘deep fake analysis’ is constantly playing catch up with media manipulators, much in the same way that drug testing authorities might be behind athletic cheats, but the gap is closing. Tools such as Cyabra and Sentinel work with security services to verify media and to analyse both its provenance and its faithfulness to the original creation. Should an item of Twitter disinformation, that originated in the far-right cluster of the Canadian COVID-19 network, contain a doctored video, then this is a crucial area of investigation in the information war. Deep fakes also, in addition to creating outright lies online, introduce doubt to genuine online content. In short, doctored media is changing how, and how much, we trust what we see, and this is undoubtably happening at different speeds in the different online groups discussing COVID-19 in Canada.

We can also use network analysis techniques to understand relationships between content according to how users traverse the platform itself. For example, we might map YouTube channels discussing the pandemic according to how the YouTube autoplay algorithm behaves, or how the platform ‘recommends’ content to users, gaining different insight to how videos are related and how the average YouTube user might be directed across the network, potentially into content wormholes. In a recent study, this technique was used to identify Turkish YouTube channels where video contributors would hold up hand-scrawled signs to indicate the codewords they intend to use in the video. Therefore, neither frame-by-frame image recognition or analysis of the audio track would have flagged that video as suspicious, despite it fraudulently linking COVID-19 to 5G base stations – a disinformation narrative that had a profound impact offline, leading to arson attacks in the UK and beyond.

Narratives

To remain relevant beyond this research, the Boolean search query that collects data that underpins the study needs to be regularly updated. This would incorporate linguistic evolution, new people, places, slang and metonyms that enter the discussion, and brand-new narratives. A clear and obvious area for further study is around the roll-out of vaccines in Canada. The immunisation drive has created a brand-new set of disinformation narratives, and brand-new tactics to disseminate them. As perhaps shown by figure 48 at the beginning of this chapter, the vaccine conversation has the potential to divide the social media network into two
deeply entrenched factions: ‘antivaxxers’ and the mainstream. Simply put, the former is much harder to reach in a polarised network compared to one of a plurality of centres of influence. There are fewer routes of engagement across the network, fewer influential liaisons that might carry ‘authoritative’ information, and a much more deep-seeded antivax ‘identity’ in that area of the network due to the sheer concentration of strong opinion and absence of dissent. If Canada wishes to exceed the proportion of the population that needs to be vaccination to achieve ‘herd immunity’, it is crucial to understand that area of the network and the qualities that allow such narratives to foster.

Provincial conversations are also important. The network created in this study shows that, online as well as offline, COVID-19 is an issue that engages people at a provincial level, with local media and political figures forming centres of influence. We might further this research to better understand COVID-19 and local level, to create more effective communications in the provinces. Due to jurisdictional boundaries, as well as the concept of influence through familiarity, we might choose not to see Canada as one online conversation around the pandemic.

Lastly, we might look at issues beyond COVID-19. Of course, this is infinitely possible for further analysis, but also to better understand the pandemic itself. For example, far right groups engaged in opposing lockdown measures and sharing narratives of disinformation: Are these social media users also sharing disinformation on other subjects? Do these other issues also form part of their ‘online identity”? Should we view the profile of this network cluster from the other direction, in that attitudes to COVID-19 could be simply a symptom of a broader online affiliation across a range of issues, than the disease itself?

In a practical sense, there is also value in understanding these tangential subjects from a monitoring perspective. Bad actors have long been known to grow a following by discussing a completely separate issue, then change tack suddenly to spread dangerous narratives. A recent study in Ukraine discovered a network of automated accounts that posted tens of millions of times over a few months about the video game Minecraft, then begin to address the war in the country’s Donbass region with increasing regularity. In short, to better understand our malign COVID-19 centres of influence and their audiences, we need to analyse what else they are doing. A basic amount of this analysis has been undertaken in this report, but it is the tip of the iceberg.

Many of these methodologies would require more computing power. The bulk of this research project was undertaken with a laptop and Microsoft Excel, largely to demonstrate that it can be done with a minimum viable product of technology and resources. However, attempting to capture large chunks of social media, create far more vast networks and apply thorough algorithms to the resulting data would require a more ambitious computing solution.
9.3 Forensic analysis

The third category of ‘next steps’ involves a more ‘forensic’ analysis of the data we have, and enrichening it with largely human processes.

The essence of this study is its ability to be scaled and automated, so that we might make sense of millions of online conversations without the impossible reliance on human analysts to pinpoint potential areas of disinformation in the network. By identifying network anomalies, and introducing human analysts to scrutinise ‘suspicious’ areas of the network, we use machines to process the quantity of information and humans to add nuance. However, there are areas where humans can go further, beyond analysis of the specific semantics and account-level detail included in public social media, and towards more forensic analysis using alternative data sources.

Whilst almost all of the methods outlined in this report might be described as Open-Source Intelligence, the field that is increasingly being called “True OSINT” takes the investigative side of such analysis much deeper. OSINT analysts follow the ‘paper trail’ of this social media activity beyond what we might see through a social listening tool, but remaining in the open-source domain, to better understand the origin and provenance of online activity, crucial in the attribution of influence operations.

This work is often painstaking and, in many ways, is the antithesis of what this project tries to achieve: scalable, mostly automated analysis. OSINT projects often requires teams of academics or seasoned researchers, working for long periods of time on one narrative or network of suspicious activity. These analysts are often skilled in exploiting the availability of metadata and even holes in a website’s attempts at opacity – the data is truly open-source, but might not have intended to be. Similarly, it might be used to identify and explore ‘mistakes’ of social media influence operations, leading to their detection. Wikipedia describes it thus:

“Open-source intelligence (OSINT) is a multi-factor (qualitative, quantitative) methodology for collecting, analyzing and making decisions about data accessible in publicly available sources to be used in an intelligence context. In the intelligence community, the term "open" refers to overt, publicly available sources (as opposed to covert or clandestine sources). OSINT under one name or another has been around for hundreds of years. With the advent of instant communications and rapid information transfer, a great deal of actionable and predictive intelligence can now be obtained from public, unclassified sources. It is not related to open-source software or collective intelligence.”
Whilst this report does not undertake true OSINT analysis methodologies, it provides a map of what we might see as opportunities, where human OSINT analysts can focus their skills. For some counter measures to be truly effective, attribution of disinformation is crucial.
The Mapping & pre-empting COVID-19 disinformation in Canada research and report was undertaken with funding from Canadian Heritage’s Digital Citizen Contribution Program.